THREE ESSAYS ON CONSERVATION: DYNAMIC AND SPATIAL RESERVE DESIGN AND VALUES AND PREFERENCES FOR ECOSYSTEM RESTORATION

BY

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DISSERTATION

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Abstract

This dissertation contributes to the growing literature on the allocation of land for conservation in three fronts. First, I create a dynamic reserve design framework that incorporates location based amenity price effects and uncertainty of development and I study the impact of amenity price effects on site selection decisions. I find that the dynamic model with price feedback effects selects sites at a lower per-site cost. The policy implication of this finding is that conservation programs should avoid purchasing land in the same neighborhood over multiple time periods.

Second, I study the public's willingness to pay (WTP) for restoring ecosystems using a choice experiment survey and I analyze the structure of preferences over ecosystem attributes. The results reveal several interesting patterns of consumer preferences and choice. First, I find that the presence of nearby existing grasslands actually increases a respondent's WTP for restoring a new grassland; this result is counter to what would be expected from neoclassical economics and can possibly be explained by endogenous preferences. Second, I find that respondents treat the conservation success measures as substitutes for each other. This latter finding implies that value-maximizing grassland design might well display corner solutions in which restoration ecologists maximize the value of a single conservation goal – producing endangered-species havens or duck factories – rather than aiming for balanced bundles of these attributes. I finally analyze the impact of including attribute interaction terms on the total willingness to pay (TWTP) and on the TWTP maximizing set of conservation success variables.

Third, in joint work with researchers from the US Army Corps of Engineers, I study the allocation of land for conservation given alternative land uses and relocation and clustering considerations using land allocation models that are applied to US military installations. I create spatial linear integer programming site selection models and apply them to selecting land for conservation of Gopher Tortoise, a key stone species currently considered ‘at risk’, at Ft. Benning GA and Ft. Stewart GA. The results show that it is possible to incorporate spatial criteria into land selection models and that conservation goals can be met in lands that are simultaneously used for military training.

I dedicate this dissertation to my parents,
two people, both of whom were first generation college students,
who overcame the odds and made the best out of life
and gave their children every opportunity possible.

The greatest happiness of thinking man is to fathom that which is fathomable and to reserve the unfathomable for reverence in quietude - Johann Wolfgang von Goethe (1749 – 1832)

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1. Introduction

1.1. Motivation

Increasing human populations result in a growing demand for urban space and land for agricultural production. This has led to an increasing conversion of natural habitats to meet human needs. More than two thirds of the area of two of the world's 14 major terrestrial biomes and more than half of the area of four other biomes had been converted by 1990 (Millennium Ecosystem Assessment 2005). Habitat loss and fragmentation is considered to be a primary cause of the current high rates of species extinction and one of the greatest threats to biodiversity (Wu et al. 2003; BenDor et al. 2009). Over the past few hundred years, humans have increased the species extinction rate by as much as 1,000 times over background rates typical over the planet's history (Millennium Ecosystem Assessment 2005).

The loss of biodiversity emphasizes the need for effective conservation of species by creating protected conservation areas and restoring endangered landscapes. Ideally, conservation areas should be set up to protect all natural biodiversity. Unfortunately, this would require a large amount of land and financial resources, both of which are scarce. For this reason, the problem of allocating land for conservation becomes an economic problem as much as it is ecological. Identifying an optimal allocation of land for conservation involves ecological and spatial aspects such as species representation, relocation, size, shape, connectivity, clustering etc., and economic considerations such as cost, budget, consumer preferences etc. (Ando et al. 1998; Margules and Pressey 2000). The first and second chapters of this dissertation analyze the economic aspects of allocating land for conservation and the third chapter studies spatial-ecological aspects of allocating land for conservation.

In addition to setting aside land as protected reserves, selecting conservation areas within land that is currently being used for alternate land use, such as military training, can achieve some conservation goals without the need to purchase land for conservation. The third chapter illustrates the above by applying site selection models to real conservation land allocation problems at Ft. Benning and Ft. Stewart in GA.

This dissertation contributes to the growing literature on the allocation of land for conservation in three fronts. First, I analyze a dynamic reserve design model that incorporates location based amenity price effects and uncertainty of development. Second, I study the public's willingness to pay (WTP) for grassland restoration using a choice experiment survey and analyze preferences over ecosystem attributes. Third, I study the allocation of land for conservation given alternative land uses and relocation considerations.

Methodologically this dissertation contributes to the reserve design, non-market valuation, and grassland restoration literatures. First, I introduce a new two-period reserve design framework that can analyze many dynamic aspects of reserve design and can incorporate uncertainty using Monte Carlo simulations. The framework is used to analyze temporal price effects in a dynamic reserve design problem where land prices in the second period may be affected by site selections in the first period. Second, I conduct a choice experiment survey to understand preferences for habitat restoration. This survey is the first non-market valuation study on grassland restoration. I use the results to analyze preferences for different measures of conservation success and to study how the presence of nearby natural areas affects WTP to provide additional natural areas. Further, I use the results to test for learning and ordering effects in choice experiment surveys. Finally, I present new reserve design models that consider species relocation, relocation distances, multiple species and multiple land use. These models are applied to real data sets to determine multiple land use scenarios involving conservation and military training.

With regard to conservation policy and management of conservation land, this dissertation provides useful guidance to policy makers and ecologists on multiple fronts. First, I show that in a dynamic world with location based amenity price effects, conservation agencies can achieve better conservation outcomes by avoiding purchasing land in the same neighborhood over multiple time periods. Second, by identifying factors which impact the public's preferences for restoration I inform policy makers to better plan restoration efforts, communicate with the public, and gather financial support. Third, I analyze how existing nearby natural areas effect the willingness to pay for restoring additional areas. Fourth I provide the first estimates of public willingness to pay to conserve and restore grassland ecosystems; this information will allow restoration ecologists and policy makers to conduct cost benefit analysis. Fifth, I highlight that the military can play a significant role in preserving biodiversity by showing that it is possible to simultaneously allocate land for conservation and military use while considering spatial and ecological needs. Finally, I present mathematical modeling formulations with spatial considerations that can be used in a solving real reserve design problems. The policy and management contributions of this dissertation are equally as important as the methodological contributions.

The first chapter titled, "Amenity Driven Price Effects in Conservation Reserve Design: A Dynamic Linear Integer Programming Approach" is collaborative work with Prof. Hayri Önal at the University of Illinois and extends the dynamic reserve design literature started by Costello and Polasky (2004) and the work by Snyder et al. (2004). I introduce a two-period dynamic reserve design framework that can incorporate location based amenity driven price effects and uncertainty in land development and species persistence. I apply the model to artificially generated data sets and compare the results with the results of an iterated static model that considers only one period at a time. I find that the dynamic model with price feedback effects selects sites at a lower per-site cost. The practical implication of this finding is that conservation programs should avoid purchasing land in the same neighborhood over multiple time periods. I test the robustness of this result under development uncertainty (or species persistence uncertainty) and find that although the two period model performs better for low levels of uncertainty as the uncertainty increases there is no significant gain in accounting for location based amenity driven prices effects.

The second chapter titled, "Estimating values, tradeoffs, and complementarities in ecosystem attributes" is collaborative work with Prof. Amy W. Ando at the University of Illinois and extends the valuation and choice experiment literature. Understanding the value of preserving and restoring ecosystem services is vital for shaping optimal conservation investments. Recent studies have shown that incorporating public preferences and economic considerations can lead to a more efficient allocation of resources. I use a choice experiment survey of Illinois residents and analyze public preferences and willingness to pay (WTP) for grasslands. I focus on grasslands because the increasing loss of grasslands in North America is a growing conservation crisis and has led to the widespread decline of bird populations that have affinities for grassland habitats. Even though there are many ecologists and conservation biologists engaged in restoring grasslands, restoration ecologists have no guidance from the economic valuation literature about the preferences people have over the characteristics of restored grasslands. If conservation agencies and organizations have information about the public's preferences and willingness to pay for grassland restoration, they will be better positioned to plan restoration efforts, to communicate with the public, and to gather financial support for projects.

I make four contributions to the non-market valuation literature. First, I estimate the values of multiple facets of grassland ecosystems. Second, I analyze how the quantity of an existing environmental public good (grasslands) affects the WTP for providing more of that good (restoring new grasslands). Third, I analyze the public's preferences and willingness to substitute between several common measures of conservation success (species richness and population density). Fourth, I test for the learning and ordering effects in choice experiment surveys. I find that species richness, population density, presence of endangered species, presence of wildflowers, and distance from a respondents home are all significant factors that affect consumers' WTP for a grassland. This finding challenges the common practice of using just one of the variables as an indicator of conservation success. I also find that the presence of nearby grasslands actually increases a respondent's WTP for restoring a new grassland. This result is counter to what would be expected from neoclassical economics and can possibly be explained by endogenous preferences. Further, respondents treat the conservation success measures (species richness, population density and endangered species) as substitutes for each other. I analyze the impact of including attribute interaction terms on the total willingness to pay (TWTP) and on the TWTP set of conservation success terms. Finally I find that there are significant learning and ordering effects in choice experiment surveys.

The third chapter is titled "Selection of Clustered Conservation Areas for Species Relocation, Multiple Species, and Multiple Land Use" and is collaborative work with Prof. Hayri Önal at the University of Illinois and Dr. James D. Westervelt, and Dr. Harold E. Balbach at the US Army Engineer Research and Development Center, Construction Engineering Research Laboratory (ERDC-CERL). The third chapter consists of three sections and broadly addresses the problem of selecting land for conservation within military installations given specific spatial considerations.

Suitable habitat areas for many rare, threatened, or endangered species in North America are in the vicinity of military installations in the U.S. While some habitat deterioration may have been caused by military training, it is often argued that the military control actually prevents those areas from destructive urban and agricultural development. Besides isolation of the lands from alternative economic use, the Department of Defense (DoD) allocates a significant amount of human capital and land for conservation efforts toward protecting and managing wildlife habitat in and around military installations. In 2006, the DoD spent $4.1 billion on environment related expenses of which $1.4 billion was for environment restoration and $204.1 million was for conservation (Benton et al. 2008).

I present methods that can allocate land for conservation given the military training needs and extend these models to incorporate various spatial and ecological criteria. The first section, titled "Optimum Selection of Clustered Conservation Areas for Species Relocation" is motivated by the need to relocate species from expanding military training areas. I present a basic relocation model, extend the model to incorporate minimum relocation distances, and apply the models to data representing Gopher Tortoise at Ft. Benning GA. The second section, titled “Optimal Selection of Conservation Lands for Dependent Species: The Case of Gopher Tortoise and Gopher Frog at Ft. Stewart, GA.” is motivated by the desire to select land that can serve multiple dependent species. I present a basic reserve selection model for Gopher Tortoise and extend it to include Gopher Frog, a species of frog that depend on GT burrows and nearby ponds. I apply the models to data from Ft. Stewart and present the results. The third section, titled “Optimum Selection of Land for Conservation and Military Use” is motivated by the need to simultaneously select both military and conservation land. I present a basic multiple use model and extend the model to include spatial criteria such as inter-cluster distances and distances to roads. I apply the model to data representing Ft. Benning GA.

The next section summarizes the motivation, research questions, methods, results and future work for each of the three chapters.

1.2. Chapter Summaries

1.2.1. Chapter 1

Title: Amenity driven price effects in conservation reserve design: a dynamic linear integer programming approach

Motivation:
1. Most conservation reserve design models presented in the literature are static and ignore the dynamic economic aspects of site selection.
2. Typically conservation programs operate under time-related (e.g. annual) budgets and purchase land over time in a sequential manner.
3. The uncertainty of land development has been incorporated in a few recent dynamic reserve selection formulations.
4. However, the existing dynamic reserve design formulations do not explicitly deal with inter-temporal price and location linkages.

Research Questions:
1. How can amenity driven price effects be incorporated into a reserve design model?
2. Does ignoring amenity driven prices effects lead to suboptimal reserves?
3. Does incorporating amenity driven price effects matter in an uncertain world?

Significance of Research Questions:
1. Understanding the benefit of including (or the risk of ignoring) price effects will allow conservation agencies and land managers to better manage their budget.
2. It is important to test the results under uncertain land availability and species persistence.

Modeling Approach: A two-period linear integer programming model, Monte-Carlo simulation

Key Results:
1. Created a modeling framework that can incorporate various aspects of dynamic reserve design models.
2. The dynamic model that incorporates amenity effects selects sites at a lower per-site cost.
3. This implies that conservation programs should avoid purchasing land in the same neighborhood over multiple time periods (concentrate on a particular area in one period).
4. Though the two period model performs better for low levels of uncertainty as the uncertainty increases there is no significant advantage in accounting for amenity driven prices effects.

Possible Further Research:
1. Extend the framework to include endogenously determined development uncertainty.
2. Test whether an option price based land purchase can overcome the effects of uncertainty.

1.2.2. Chapter 2

Title: Estimating values, tradeoffs, and complementarities in ecosystem attributes

Motivation:

1. Understanding the value of preserving and restoring ecosystem services is vital for shaping optimal conservation investments.
2. Recent studies have shown that incorporating public preferences and economic considerations can lead to a more efficient allocation of resources.
3. We use a choice experiment survey of Illinois residents and analyze public preferences and willingness to pay (WTP) for grasslands.

Research Questions:

1. Understand the consumers' preferences and WTP for grassland restoration?
2. Do different conservation success measures act as substitutes or complements?
3. How is the public's WTP for habitat restoration affected by nearby natural areas?
4. What characterizes the total willingness to pay maximizing grassland.
5. Are their learning and ordering effects in choice experiment surveys

Significance of Research Questions:

1. Fill a gap in the valuation literature by identifying the WTP for grassland.
2. Inform conservation agencies about the public's attitudes towards various attributes of ecosystems and measures of conservation success.
3. Analyze how existing natural areas affect the willingness to pay for new areas.

Modeling Approach:

Choice experiment survey, analysis using a mixed multinomial logit model

Key Results:

1. Species richness, population density, presence of endangered species, presence of wildflowers, and distance from a respondents home are all significant factors that affect respondent's WTP for a grassland.
2. Nearby grasslands actually increases a respondent's WTP for restoring a new grassland.
3. Including attribute interaction terms results in convex TWTP contours.
4. Respondents treat the conservation success measures (species richness, population density and endangered species) as substitutes for each other.
5. We find significant learning and ordering effects.

Ongoing Work:

1. Create an econometric specification that provides interaction terms with desired properties.
2. Account for possible endogeneity in the grassland near variable in the econometric estimation.

1.2.3. Chapter 3

Title: Selection of clustered conservation areas for species relocation, multiple species, and multiple land use
in the Journal of the Military Operations Research Society

Motivation:

1. The last remnants of suitable habitat areas for many rare, threatened, or endangered species in the U.S. are in the vicinity of military installations and the Department of Defense (DoD) allocates a significant amount of human capital and land for conservation efforts.
2. At the same time the need for new and conventional training is growing and leads to increasing pressure to manage federal lands by balancing competing objectives and land uses.
3. This chapter introduces linear integer programming formulations that consider species relocation distances, multiple species, and multiple land use.
4. The formulations are applied to the selection of clustered conservation areas within the boundaries of military installations.

Research Questions:

1. Identify the optimal selection of sites for conservation given the alternate land use
2. How can relocation considerations be included in designing conservation management areas within military installations and reserve design models in general?
3. How can multiple land use considerations be included in reserve design models?

Significance of Research Questions:

1. Optimally selecting conservation areas within the military installation allows endangered species to be managed effectively while decreasing the impact on the military mission.
2. Incorporating ecological criteria such as movement distance and meta-clustering allows for better design of conservation areas.
3. Including multiple species and multiple land use considerations can lead to more efficient conservation outcomes.

Modeling Approach: Linear integer programming models, GIS tools

Key Results:

1. New reserve design models (a clustered relocation model, a minimum distance relocation model, a multiple species model, and a multiple land use model)
2. The models are applied to a dataset related to Gopher Tortoise (GT), a key stone species currently considered ‘at risk’, at Ft. Benning Georgia
3. The solutions of the models are consistent with intuition and reflect the desired outcomes
4. There is a trade-off between spatial considerations and minimum habitat size
5. There is a trade-off between various spatial considerations

1.3. References

Ando, A., Camm, J. D., Polasky, S. & Solow, A. 1998. Species distribution, land values and efficient conservation. Science, 279, 2126-2128.

BenDor T., Westervelt J., Aurambout J.P., Meyer W. 2009. Simulating population variation and movement within fragmented landscapes: An application to the gopher tortoise (Gopherus polyphemus), Ecological Modelling, Volume 220, Issue 6, 24, Pages 867-878.

Benton, N., J.D. Ripley, and F. Powledge, eds. Conserving Biodiversity on Military Lands: A Guide for Natural Resources Managers. 2008 edition. Arlington, Virginia: NatureServe. Available at http://www.dodbiodiversity.org.

Costello, C., Polasky, S., 2004. Dynamic reserve site selection. Resource and Energy Economics, 26(2), 157.

Margules, C.R., Pressey, R.L. 2000. Systematic conservation planning. Nature 405, 243–253.

Millennium Ecosystem Assessment 2005. Ecosystems and human well-being: Biodiversity synthesis. World Resources Institute, Washington, District of Columbia.

Wu, J., Huang, J., Han, X., Xie, Z., Gao, X., 2003. Three-gorges dam-experiment in habitat fragmentation. Science 300, 1239–1240.

Snyder S., Haight R. G., ReVelle C. S., 2004. A scenario optimization model for dynamic reserve site selection. Environmental Modeling Assessment 9(3): 179.

2. Amenity Driven Price Effects and Conservation Reserve Site Selection: A Dynamic Linear Integer Programming Approach

Most conservation reserve design models presented in the literature are static and ignore the dynamic economic aspects of site selection. Typically conservation programs operate under time-related (e.g. annual) budgets and purchase land over time in a sequential manner. The uncertainty of land development has been incorporated in a few dynamic reserve selection formulations using stochastic dynamic programming. However, the existing formulations do not explicitly deal with inter-temporal price and location linkages. We address this issue here and present a two-period linear integer programming model for conservation reserve design that incorporates amenity driven price feedback effects inherent in the reserve development problem. In addition, the model includes spatial and ecological criteria. We then use this model to answer the question "How suboptimal is ignoring amenity driven price effects in reserve design models?" We apply the model to artificially generated data sets and compare the results with the results of an iterated static model that considers only one period at a time. We find that the dynamic model with price feedback effects selects sites at a lower per-site cost. The policy implication of this finding is that conservation programs should avoid purchasing land in the same neighborhood over multiple time periods.

2.1. Introduction

Increasing human populations result in a growing demand for urban space and land for agricultural production and this has led to an increasing conversion of natural habitats and to a decrease in biodiversity. Costello and Polasky (2004) highlight these changes as "Only about fifty percent of the forest area that existed at the time of the rise of agriculture remains, of which less than half remains in large tracts capable of sustaining a full range of biological diversity." Further, globally intact ecosystems are being converted to other uses at a rate of one percent per year (Balmford et al. 2002; Meir et al. 2004). The resulting loss of biodiversity emphasizes the need for effective protection of species by creating reserves which are known as the most effective tools for biodiversity conservation (Possingham et al. 2006). Ideally conservation reserves should be established to protect all natural biodiversity (Margules and Pressey 2000; Polasky 2006). Unfortunately, this would require a large amount of land and financial resources, both of which are scarce (James et al. 1999). For this reason, the conservation reserve design problem becomes an economic problem as much as it is ecological.[1] Conservation programs have limited budgets and limited scope; therefore, it would be desirable to optimally select the land areas that best serve the ecological needs given the budget constraint.

The existing reserve selection literature focuses mostly on static designs, assuming that site selection decisions are to be made all at once, and therefore ignore the dynamic economic feedback effects (Meir et al. 2004; Naidoo et al. 2006; Armsworth 2006). In reality, however,

[1] In an analysis of funding for the world's 34 terrestrial ''biodiversity hotspots'' Bode et al. (2008) find that variations in cost and threat are more significant than ecological factors in determining funding allocations. Ando et al. (1998) and Naidoo et al. (2006) highlight the importance of incorporating economic costs into conservation planning

conservation programs purchase land over time and are subject to annual budget availability (McDonald-Madden et al. 2008; Possingham and Wilson 2005). The probability of land development for non-conservation (e.g. urban or industrial) use and the value of land prices in later periods may be influenced by choices made in initial periods (Meir et al. 2004; Costello and Polasky 2004; and Harpankar 2006). Spatial aspects, such as clustering, compactness, adjacency, and contiguity of sites are important considerations in reserve design since effective functioning of a reserve is directly related to the spatial coherence of selected sites. Therefore, for conservation planners the value of land parcels adjacent to previously established reserve areas is typically higher than the value of non-adjacent parcels. This is likely to increase the future market values of those lands because of speculative supply behavior of land owners. Moreover, proximity of land parcels to nature reserves often increases the demand for those lands, and therefore the prices, due to their amenity value. Incorporating these effects in site selection may change the optimal land acquisition decisions over time and thus the configuration of the reserves. Existing dynamic reserve selection formulations presented in the literature deal with uncertainty in land availability, but no study explicitly incorporated linkages between inter-temporal price changes and location of selected and future reserve sites in a dynamic optimization framework (Armsworth et al. 2006; Naidoo et al. 2006).

The present paper addresses the above mentioned issues and introduces a two-period linear integer programming model for dynamic reserve site selection. The model: i) incorporates economic feedback effects inherent in site selection by accounting for location based amenity driven price changes (hereafter termed as the *price premium*) in second-period land prices based on the first-period site selection decisions; and ii) includes spatial and ecological criteria when determining the sites to be selected in both periods.[2] We use the model to answer the question "How suboptimal is ignoring amenity driven price effects in reserve design models?" by comparing the two-period (forward-looking) model results with the results obtained from a sequentially solved static (myopic) model that considers only one period at a time. The simulation findings demonstrate that the forward-looking model with price feedback effects selects sites at a lower per-site cost and is able to select more habitat than the myopic model. This is achieved by concentrating the selected sites over one sub-area in each period to the extent possible. The practical implication of this finding is that conservation programs should focus on a particular geographical area for land acquisition in a given time period, rather than spreading the purchases over multiple areas in the same period, to avoid excess cost resulting from price premiums[3]. We also present a sensitivity analysis and test the robustness of the results by conducting a Monte Carlo simulation for stochastic land suitability over a range of price premiums. We find that the results hold for a range of amenity driven prices changes and that the difference between the forward-looking two-period model and iterated one-period model increases as the amenity driven price premium increases.

2.2. Literature Review

Optimal site selection methods range from heuristics to mathematical programming. Even though heuristics are practical and can incorporate complex site selection criteria, sub-optimality of the solutions is a major concern (Önal 2004; Moilanen and Ball 2009).

[2] The price effect in (i) can also be interpreted as an 'option price' that conservation planner would be willing to pay in order to secure the availability of preferred land parcels against development uncertainty.

[3] This result holds strongly for scenarios with high amenity prices and low risk of species extinction by the next period. If the price premium values are low (for example for marginal land) or if the risk of species extinction by the next period is high then the focus should be on protecting areas with high risk of species loss.

Mathematical programming, on the other hand, can be computationally complex, but it is useful for determining an exact optimum solution (Önal 2004; Haight and Snyder 2009). This approach has been used extensively in the reserve site selection literature using the set covering and maximal covering formulations introduced by Toregas and ReVelle (1973) and Church and ReVelle (1974). Numerous static linear integer programming models have been presented to select optimal conservation areas given ecological criteria and conservation resource (financial) limitations (see, for example, Kirkpatrick 1983; Underhill 1994; Camm et al. 1996; Church, Stoms and Davis 1996; Ando et al. 1998; Possingham et al. 2000; Rodrigues and Gaston 2002). Typically the solutions of both the set covering and maximal covering formulations result in scattered sites and lack spatial coherence, which may impede effective functioning of the selected habitat areas and increase the cost of management. Several studies presented in the past decade extended the basic set covering and maximal covering formulations to incorporate various spatial criteria in site selection such as boundary length minimization, clustering, connectedness, compactness, contiguity, etc. (e.g., Williams and ReVelle 1996, 1998; Cova and Church 2000; Williams 2002; Fischer and Church 2003; Önal and Briers 2003, 2006; Cerdeira et al. 2005; Önal and Wang 2008; see Williams et al. 2005 for an extensive review).

Static optimal site selection models work with a snapshot of the problem, assuming a fixed availability of land, a fixed distribution and biodiversity of species, fixed prices, immediate implementation of the results and upfront availability of the total budget (Meir et al. 2004). These assumptions may not always be realistic due to various reasons: i) conservation organizations have annual budgets and are forced to make purchase decisions on an annual basis; ii) species populations and distributions may vary with time, where some species might migrate, become extinct or relatively safe, thus conservation priorities may change over time; iii) the land market conditions may change over time, namely prospective sites might get developed (thus unavailable for conservation) and land prices may change. Recently there has been significant interest in studying such issues and dynamics of optimal site selection. Various approaches have been used for this purpose, including formal optimization, specifically stochastic dynamic programming (Costello and Polasky 2004; Strange et al. 2006; Sabbadin et al. 2007) and integer programming (Snyder et al. 2004), constrained Markov decision processes (Newburn 2005; Newburn 2006), meta-population modeling (Moilanen 2002), and heuristics (Costello and Polasky 2004; Strange et al. 2006; Snyder et al. 2004).

Costello and Polasky (2004) opened the field of dynamic conservation reserve design using formal optimization. They formulated the problem as a stochastic dynamic programming model assuming that the conservation agency aims to maximize the number of protected species at the end of the planning horizon under a given annual budget and probability distribution for the availability of individual land parcels for acquisition in each period. The selection of sites in each period affects the probability of future survival of species, whereas the sites that are not selected in any period face some probability of irreversible conversion to non-conservation development in the subsequent periods. A small-scale empirical application of the model shows that a larger conservation budget in the beginning would result in greater conservation benefits and that better results may be achieved with a small initial budget than allocating a larger budget later. Strange et al. (2006) extended the model introduced by Costello and Polasky (2004) to allow for selected sites to be sold in later periods (when those sites are not needed for conservation anymore) and showed that a model with this swapping option performs better than the original model.

Stochastic dynamic programming (SDP) is computationally complex due to the well-known 'curse of dimensionality'. The complexity increases exponentially as the number of parcels considered increases[4]. For this reason Costello and Polasky (2004) applied this approach to problems with up to 10 parcels and 6 periods only. Sabbadin et al. (2007) introduced a SDP model that accounts for contagion risk of deforestation, but again the model was applied to small problems with less than 10 parcels. Meir et al. (2004) emphasize that the SDP model becomes computationally impossible above about 20 sites. Therefore, the SDP method is not practically applicable to real-world, large-scale conservation reserve design problems. Snyder et al. (2004) formulated the reserve design problem using a two-period integer programming framework to incorporate development uncertainty by considering a set of possible scenarios each of which involves a second-period development outcome. Specifically, their model assumes a 50 percent probability of development for each of 146 sites and considers a randomly generated set of 100 development scenarios. Based on their computational experiences with the model, the authors claim that this approach is applicable to large data sets as well.

An important dynamic aspect of land acquisition is the change in land prices over time which might occur as a consequence of earlier site selection decisions. The static models presented in the reserve design literature and the dynamic models mentioned above ignore this type of economic feedback effect (Costello and Polasky 2004; Naidoo et al. 2006). Costello

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[4] For instance, Strange et al. (2006) find that the model grows exponentially in size at a rate of 3^J, where J is the number of parcels.

and Polasky (2004) and Harpankar (2006) list such effects as increases in: 1) the price of remaining land parcels due to the reduced supply of land; 2) the price of land parcels adjacent to the reserves (price premium) due to the amenity effect of being close to conservation reserves that may attract urban development more in those areas.

The increase in property values due to the amenity effect of being near to open spaces and protected areas has been analyzed extensively in other contexts but not in the context of conservation reserve design. Irwin (2002) conducts a hedonic analysis of the impact of open space on the value of neighboring residential properties and finds that both privately owned conservation lands and publicly owned open space have a positive effect while privately owned forests have a negative effect. Neumann et al. (2009) study the amenity value of proximity to a National Wildlife Refuge (NWR) in central Middlesex County, Massachusetts, and find that a property located 100 meters closer to the NWR than another neighboring property has a price premium of $984.00[5] in 2007 dollars. For a review of studies on the impact of open space on property values see McConnell and Walls (2005).

The urban planning and urban development literature analyzes a related problem of urban development given environmental amenities. Wu (2001) and Wu et al. (2004) analyzes the effect of open space and other amenities on housing prices and development density within the framework of an urban equilibrium model. Wu and Irwin (2008) solve a spatially explicit dynamic model of land development that incorporates water quality as an environmental amenity. Tajibaeva et al. (2008) study the provision of open space in metropolitan areas using a closed city and open city discrete-space urban model. The above papers, as well as this strand

[5] per 100 meters per property.

of the urban development literature, analyze the optimal development patterns given the presence of environmental amenities and is focused on the use of land for urban development. Our paper on the other hand is extending the reserve design literature and incorporates conservation based amenity price premiums into a reserve design framework that is optimally identifying the sites to protect for conservation.

This paper addresses the price premium effect mentioned above and introduces a mathematical model that incorporates this type of effect in conservation reserve design and land acquisition decisions. The amount of the effect is determined by exogenous factors, such as the type of conservation activity, access to recreation, etc. However, since the optimum selection of sites (both the number of selected sites and their location) might be altered by the price premium the total cost to the conservation agency becomes endogenous. Note that this paper is not a land market equilibrium analysis incorporating demand and supply of land and endogenous land prices in a competitive market, as analyzed by Armsworth (2006). The latter is static in the sense that it considers one period and illustrates a price change in the land market due to an increase in demand for land. The amenity-driven price effect addressed in this paper, on the other hand, is a location based effect that only applies to parcels that are adjacent to the lands purchased in previous periods.

An overview of the model is presented in the next section. The algebraic details and an explanation of the workings of the model are given in Appendix A.

2.3. Methods

We first introduce the terminology that is used in the model development and throughout the rest of the paper and then describe the key components of the model. The full model is provided in Appendix A. The ecological benefit from selecting an individual site, e_k, is measured using a *habitat suitability index*, which can be defined differently in different applications[6]. In a single species analysis the simplest measure can be the carrying capacity, namely the maximum number of individuals that can be supported by each site, depending on the soil types, vegetation, access to water sources, slopes and various other physical and ecological considerations. When multiple species are involved a different suitability index needs to be defined for each site and each species (for an example see Cowling et al. 2003). In this case, the second summation in the objective function (total suitability) needs to be modified where suitability is summed across the species as well (using possibly differential weights). Alternatively, a 'covering' constraint can be imposed for each species where the protected population of that species is restricted to exceed a specified minimum and the carrying capacities of selected sites determine the protected population of that species. The term *site* is used for indivisible land parcels with known ecological and economic characteristics. Each site may be a cell in a grid partition or a piece of land with specified boundaries. A *reserve* is a spatially coherent set of sites that collectively serve as a habitat area for a specified set of species. For spatial coherence, here we require that the sites forming a reserve to be as tightly packed as possible, or clustered, around a *central site* in that reserve. This spatial consideration

[6]The ecological suitability parameter is assumed to be independent across sites (i.e. there is no spatial autocorrelation between the habitat suitability of sites), a standard assumption in the reserve site selection literature.

is incorporated in the model by minimization of the distances between all sites in a reserve and the central site of that reserve, which leads to a compact (circular or square-like) reserve configuration. Such reserves are believed to function more effectively than dispersed reserves where sites are scattered over a large geographical area. Clustered reserves facilitate dispersal and colonization of species among adjacent or nearby sites, which generally enhances the long-term persistence of species (Harrison 1994; Hanski and Simberloff 1997). Finally, we define a *reserve system* as a collection of reserves that together serve some stated conservation purposes.

The objective function of the model consists of two components. The first component achieves clustered reserves and the second component maximizes the total amount of ecological suitability from the selected sites. The two non-compatible objectives in the objective function are multiplied by appropriate weights, representing their significance in site selection decisions, to obtain a unified objective function.[7] We allow the model to select more than one reserve since in practice conservation agencies focus on multiple biodiversity hotspots in different regions or areas. From an ecological point of view having multiple reserves ensures distinct and separate populations, managerial efficiency, and lower invasive potential.

The budget constraint is specified separately for the first and second periods. Typically, conservation agencies and government organizations engaged in conservation are required to spend their allocations annually and in some cases any unspent budget will result in a decrease

[7] In reality spatial configuration and quality of the selected habitat can be related, but this relationship will depend on the specific application. If the model is being applied to a specific set of species or a specific ecosystems where the relationship between habitat quality and spatial pattern is known, that information can be used to generate an objective function with a single metric.

in future budget allocations. Therefore, we exclude the possibility of a budget carry over.[8] The first period budget constraint limits the total cost of land acquisition to the available budget in the first period, where each site is priced at the 'regular' land market price p_1. We assume that the land purchase occurs in a competitive market and that the first period land market price incorporates any information about the ecological suitability of the land that the land owners may have.[9]The second period budget constraint also incorporates an amenity driven price premium in addition to the 'regular' land market price in period 2 if an adjacent site has been selected in the first period. We use three market clearing land prices, p1, p2 and p3 within the model. If the land price before the conservation agency entered the market is p_0, we consider the first period market price given by

p_1 = p_0 + price increase due to period-one land market effects resulting from land purchases for conservation.

We then consider two components for the second period market price given by

p_2 = p_1 + price increase due to period two land market effects

p_3 = p_2 + location based amenity price effects, denoted by p_a, for sites that are adjacent to first period purchases.

[8]The model can be modified to incorporate budget carry over possibility as indicated in Appendix A. We had relaxed this assumption of no budget carry over in initial runs and allowed the budget to be carried over. When the base price (without premium) is assumed to remain unchanged in the two periods the model resulted in the trivial solution where all sites were selected in the second period. This makes sense since selecting all sites in the second period avoids paying a price premium that could occur otherwise. If the second period base price is greater, the model purchases sites in both the first and second period. The number of site selections delayed to period 2 depends on the relative values of price premium and base price differences in the two periods.

[9] The price premium that we describe is a price increase due to a spatial amenity effect (when a conservation agency purchases land in the first period the value of the surrounding land increases). The price premium does not reflect landowners having information about the ecological suitability of the land. We assume that price effects due to land owners having information about the ecological suitability of land will be reflected in the initial land prices. If the landowners had prior knowledge of the ecological suitability of their land then their first period land prices will be higher and the model can account for heterogeneous prices. We relax this assumption in one of the sensitivity analysis in the results section and show that the results are still valid.

We assume that p_1 and p_2 are known and the price premium, p_a, is given as an exogenous parameter, determined by factors such as location, the type of conservation, access to recreation etc. Implementing this pricing mechanism requires the site selection model to endogenously identify the second period sites that are adjacent to first period selections and subject to the price premium.

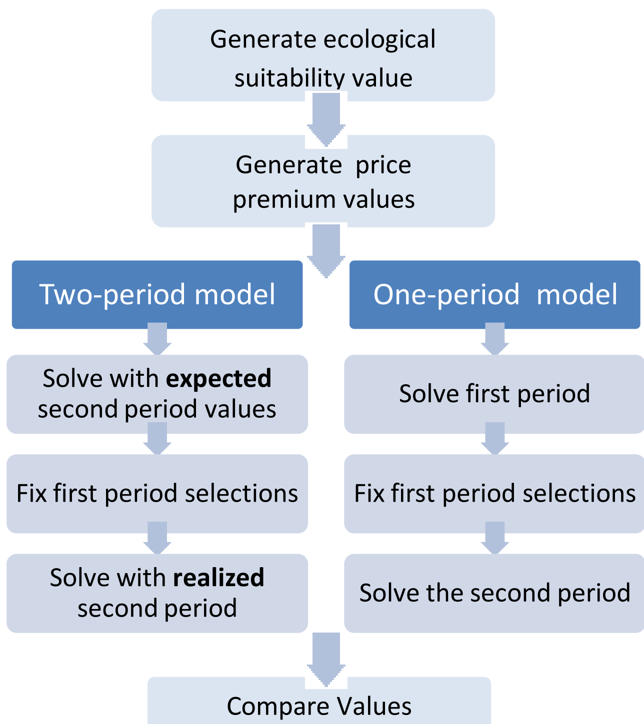
The site selection problem with the considerations mentioned above is formulated here as a mathematical programming model, specifically an integer program. For readability we present the explicit algebraic description of the model and explanation of the individual model constraints in the appendix. This formulation extends the current literature on dynamic reserve site selection in two directions. First, the model allows for location based amenity driven price premiums to be considered in multi-period site selections by endogenously identifying the sites subject to the price premium. Second, it ensures that the selected sites form a spatially coherent reserve system including *n* compact reserves each including a set of clustered sites around a central site.[10]

2.4. Application and Results

We first apply the above model to a randomly generated data set including a 20x20 grid partition, where each grid cell represents a site (thus a total of 400 sites is considered). As presented, the two-period model assumes perfect information about the second period prices and the price premiums, which would bias the comparison with an iterated one-period model that selects sites in a myopic way by consideration of the current period prices only. To remove

[10] Minimum viable population requirement can be incorporated for individual reserves as well as the entire reserve system as indicated in Appendix A.

this bias, we simulate an imperfect information situation using the two-period model by first using the expected values for second period prices to find the first period selections and then rerunning the model with the actual second period prices and first period selections. This ensures that both the two-period model and the iterated one period model use the same information. The simulation was conducted according to the following algorithmic procedure where both models used the same set of randomly generated data.



Using the same set of randomly generated data for both models in each run allows for the comparison of the differences in the results of each run as well as the difference across all runs. Using expected prices in the first period of the two-period model ensures that the first period decisions are made without perfect information about the second period, as would be done in real world planning. The conservation planner is assumed to know the distribution of the second period prices and therefore the expected value of second period prices. We illustrate a specific scenario for one and two reserves and then present a Monte Carlo simulation and then extend the simulation to include uncertainty of site availability.

2.4.1 Results

The ecological suitability values for individual parcels were randomly chosen from a uniform (0, 5) distribution. The following parameters were used with the model: area = 400 square cells in a 20x20 grid, p_{1k} = 1.00, p_{2k} = 1.00, p_{ak} = 0.50, α_1=1, α_2=1[11], first period budget = 10, second period budget = 15.[12]

Figure 2.1 and Figure 2.2 compare the results for the two-period model and an iterated one-period model for selecting two reserves (n=2) and one reserve (n=1) respectively. Figures 1.a and 2.a display the results for the iterated one-period model and Figures 1.b and 2.b display the results for the two-period model. The first column identifies the individual reserves selected by the model[13], while the second column identifies the time period that the sites were selected.

As shown in Figure 2.1 the iterated one-period model selects 10 sites providing 49 ecological suitability units in the first period at a cost of 10 currency units (say in million dollars-$M) and 12 sites with 54 ecological suitability units in the second period at a cost of 15 $M.

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[11] See the appendix for an explanation of the symbols.

[12] Although we use homogeneous prices and price premiums in the present analysis (each site has the same price and second period price premiums), the model allows for heterogeneous prices and price premiums. Also we assumed that the second period prices remain unchanged for those sites that are not adjacent to first period selections. Increasing the second period base prices did not change the relative results (namely, the absolute coverage decreased, but the two-period model continued to perform better than the iterated one-period model).

[13] In the present analysis we have not included contiguity as an explicit requirement when defining a 'reserve'. Rather, we define a reserve as a 'collection of spatially coherent sites' (see p.7) and use compactness as a requirement for spatial coherence. Reserve design models that require compact clusters, either by minimizing distances to a cluster center or by minimizing boundary length may result in disconnected sites. Therefore the results shown in Figures 1 and 2 include multiple disconnections. The reserves that each site belongs to are labeled using 'A' and 'B' in Figure 1 and Figure 3. Contiguity can be included in a programming model following the methodology presented by Önal and Briers (2006).

Therefore, the iterated one-period model provides 4.12 ecological suitability units per unit spending[14] (0.242 $M per ecological suitability unit). In contrast, the forward looking two-period model selects 10 sites providing 44 ecological suitability units in the first period and 15 sites with 71 ecological suitability units in the second period using the same amounts of budget as the iterated one-period model. Therefore, though the two-period model selects a lesser amount of ecological suitability in the first period, and it selects a greater amount of ecological suitability than the iterated one period model over the two periods. The two-period model provides 4.6 ecological suitability units per unit spending, 12% more than the iterated one-period model over the two time periods. These results show that the two-period model that accounts for location based amenity driven price effects clearly performs better. As can be seen in the second column of Figure 2.1, the difference occurs because the two-period model avoids paying a higher price in the second period by locating the second period selections away from the first period selections. The iterated one-period model maximizes the first period coverage without considering the subsequent (and possibly adverse) effects on payments in the second period. As a result, a higher price (premium) is paid for six of the sites selected in the second period (the cells that are marked with thicker edges in Figure 2.1). The budget limitation and the price premium paid in the second period allow selecting only 12 sites in the second period. The forward looking two-period model, on the other hand, allows selecting 15 sites in the second period with the same amount of budget and without paying the price premium for any site[15]. Note that the two-period model covers less ecological suitability units in the first period

[14] (49 + 54) / (10 + 15) = 103/25 = 4.12.
[15] In this case no adjacent site was selected in the second period, but this may not be the case in other instances (see for example the one-cluster case in Figure 3.b).

because the first period decisions take the expected second period price premiums into account. For the one cluster case, the forward looking two-period model selects 4% percent more ecological suitability units per unit spending than the iterated one-period model.[16,17] The above results were generated from one randomly generated set of ecological suitability values for an exogenously specified price premium value. Therefore it is necessary to check the robustness of the results before making a general conclusion based on these results.

2.4.2 Monte Carlo simulation and Sensitivity Analysis

To analyze the robustness of the above results we conducted a Monte Carlo simulation and compared the results obtained from the two-period model and the iterated one-period model where price premiums paid for adjacent sites purchased in the second period are stochastic (but with a known distribution function). Again the ecological suitability assigned to each site was randomly chosen from a uniform (0, 5) distribution to avoid any possible bias in spatial distribution of site characteristics. The following parameters were used in the simulation; area = 100 sites, where each site is a cell in a 10x10 grid partition, p_{1k} = 1.00, p_{2k} = 1.20, price premium $p_{ak} \sim U$ E(P_{ak}) = 0.50, α_1=1, α_2=1, n=2, b_1 = 10, b_2= 20.

Table 2.1 displays the results of the two-period model and the iterated one-period model given stochastic land suitability and second period prices, where the second period price

[16] For the one reserve case and same budget availability, the iterated one-period model selects 10 sites with 48 ecological suitability units in the first period and 13 sites with 56 ecological suitability units in the second period (Figure 5), which corresponds to 4.16 ecological suitability units per unit spending. The forward looking two-period model, on the other hand, selects 10 sites with 47 ecological suitability units in the first period and 14 parcels with 61 ecological suitability units in the second period, providing 4.32 ecological suitability units (4 percent more) per unit spending.

[17] Again two-period model performs better since the iterated one-period model pays a higher price for 4 sites selected in the second period (allowing selection of 13 parcels), whereas the forward looking two-period model pays a higher price for only one site selected in period two, thus allowing selection of 14 sites with the same amount of budget.

premiums were chosen from a uniform (0, 1) distribution. The first column in Table 2.1 displays the second period price premium statistics, columns 2, 3, 4 and 5 display the total cost, total number of selected sites, first period ecological suitability and total ecological suitability, respectively. Column 6 represents the clustering (compactness) value, which is calculated as the sum of distances from all sites in the reserves to the corresponding reserve, and the last column represents ecological suitability per unit conservation budget spent.

The Monte Carlo simulation produces similar results to those presented in section 4.1, indicating that the two-period model consistently performs better in terms of economic/ecological efficiency in site selection. On average, the two-period model with imperfect information selects 25.87 sites at a total cost of 29.47 $M covering 111.18 ecological suitability units with a clustering value of 45.44 and a coverage of 3.77 ecological suitability units per unit budget spent. The iterated one-period model, on the other hand, selects 23.550 cells (on average) at a cost of 29.277 $M, covering 102.14 ecological suitability units with a clustering value of 43.842 and a coverage of 3.49 ecological suitability units per unit budget spent. By definition, the reduced clustering value (smaller total distance to the reserve centers) indicates a more compact reserve configuration, but this comparison is meaningful only if the two reserves have the same size. The higher clustering value obtained with the iterated two-period model does not mean that the reserve is less compact than the reserve configuration found by the one-period model since fewer sites are selected in the latter[18]. Similar to the one and two-cluster cases presented above, the forward looking two-period model performs better overall by covering relatively less habitat in the first period to minimize the number of parcels

[18] If the clustering value is averaged over the number of sites selected, then the two-period model has a lower per unit clustering value (specifically, 1.75 for the two-period model and 1.86 for the one-period model).

on which it pays the price premium in the second period. The two-period model covers 42.53 ecological suitability units on average in the first period whereas the one period model covers 47.65 ecological suitability units on average in the first period. Since the same randomly generated data were used with both models, it is meaningful to analyze the differences between the models for each run. The last section in Table 2.1 presents the mean, standard deviation, T-statistic and the p-values for the significance of the differences between the results of the two models. For the 100 runs performed in the Monte Carlo simulation, the two-period model covered 9.040 more ecological suitability units than the iterated one-period model (8.85% increase), with a standard deviation of 6.5, and the two-period model covered 0.28 more ecological suitability per unit spending than the iterated one-period model (8.08% increase), with a standard deviation of 0.21. The p-values for the hypothesis test for significance of the difference between the two-period model and the iterated one-period model indicate that the two-period model performs better than the iterated one period model at a significant level of 0.0001. These findings demonstrate the robustness of the results obtained from the two models.

Though the results presented here are for a Monte-Carlo simulation for two clusters, the results with varying number of clusters were consistent with the above results. Specifically, we performed the Monte Carlo simulation for both one-cluster and three-cluster cases. We found that as the number of clusters increases the difference between the two-period model and the iterated one-period model increases as well. For instance, for the three-cluster case the two-period model covers 9.3% more ecological suitability and 9.8% ecological suitability per unit spending. The results are also sensitive to the choice of the base second period price resulting from the land market changes. We performed the Monte-Carlo simulation where both the first and second period base prices were kept at 1.00. The results show that for the two-cluster case the two-period model outperformed the iterated one-period model by 11.7% for ecological suitability and 10% for ecological suitability per unit spending.

Given that the second period price premium is exogenously specified, rather than being based on actual prices in land markets, it is meaningful to analyze robustness of the results over varying ranges of price premiums. Figure 2.3 depicts the differences in ecological suitability of selected reserves between the two-period model and the iterated one-period model as a function of the second period price premium. The results demonstrate that as the price premium increases the differences between the two models increase, and at all values of the price premium the two-period model consistently performs better than the one-period model.

The above mentioned values (8.85%, 8.08%, 9.3%, 9.8%, 11.7%, and 10%) are sensitive to the spread of the price premium being considered in the simulation. We performed 1000 Monte Carlo simulations to analyze how the results are dependent on the spread of the price premium. Table 2.2 presents the percentage improvement in the ecological suitability and ecological suitability per unit spending of the two-period model over the one-period model for varying ranges of price premiums. The results illustrate that as the range of possible price premiums increase the improvement of the two-period model also increases.

We initially assumed homogenous first period prices. In response to a reviewer's suggestion we relax this assumption and conduct a sensitivity analysis by conducting 1000 Monte Carlos runs where we assume the land owners might have information about the ecological suitability of the land and therefore charge a higher price for lands with high ecological suitability. For this sensitivity analysis we assumed that the first period price would be the sum of a uniform base price, p_{1bk}, and an ecological premium, p_{1ek}, which is a linear function of the ecological value of the land.[19] We set p_{1bk}=0.9 and an ecological premium, p_{1ek} =ek/20 to obtain an $E(p_1 = p_{1bk} + p_{1ek})=1$ which is identical to the previous scenarios. The results are presented in Table 2.3 and highlight that the two-period model continues to perform better than the iterated one-period model even when heterogeneous initial prices that are dependent on the ecological value of the land two-period models are considered. Comparing Table 2.1 and Table 2.3 reveal that when ecological value dependent initial land prices are considered the differences (in the amount of total ecological suitability) between the two-period model and the iterated one-period model is less than under the scenario with homogenous first period prices but importantly the results emphasize that accounting for amenity price premiums can improve the total amount ecological suitability protected under a given budget.

The above results present another instance of encountering sub-optimality when in each step the best decisions are made myopically without considering the consequences in future steps. In this particular case, the iterated one-period model selects the best sites in the first period with the given budget disregarding the possible adverse impacts of the first-period selections on the price premiums to be paid in period two, whereas the two-period model forgoes purchasing some good sites in the first period[20] to avoid paying a price premium. An important and practical policy implication of this finding is that a conservation planner would

[19] The ecological price premium is based on the ecological suitability of the land and reflects the land owner having prior information, it is distinct from the amenity price premium we discuss in this paper, the amenity price premium is a results of the conservation organizations first period choices and only impacts the sites adjacent to sites purchased in the first period.

[20]In the two reserve case, the iterated model selected 49 ecological suitability units in the first period, whereas the two-period model selected only 44 units in the first period. In the one reserve case, the iterated model selected 48 ecological suitability units in the first period, whereas the two-period model selected 47 units in the first period.

do better by focusing on one area in each period. By doing so the planner may not have to buy land in the same area in the future and would avoid paying price premiums for parcels that are adjacent to previous period selections. The contrary, spreading the land purchases in a given period, would increase the likelihood of selecting adjacent pairs of sites in subsequent periods, since spatial considerations such as clustering and contiguity may favor the selection of those sites, and therefore the total cost. The approach presented here would improve the economic efficiency of site selection decision making. The extent of the improvement depends on the price premium, conservation budget and ecological characteristics of individual sites.

2.4.3 Analysis of Objective Function Weights

In general, results from multi-objective optimization programming models are sensitive to the specification of weights assigned to different objective functions. Figure 2.4 presents the results obtained from the two-period model with different weights assigned to the clustering and ecological suitability attributes. The following parameter values were used in the test runs; total number of sites = 400 (cells in a 20x20 grid), p_{1k} = 1.00, p_{2k} = 1.00 p_{ak} = 0.50, n=2, b_1= 10, b_2= 15. The selections displayed in column (a) show the results with equal weights for the two components of the objective function ($\alpha_1 = \alpha_2 = 1$). Column (b) shows the results where the weight for the clustering component, α_1, is increased from its initial value of 1 to 2 and α_2= 1 (α_1= 2 and α_2 = 1). Column (c) displays the results where the weights for ecological suitability, α_2, is increased from 1 to 10 and α_1= 1 (α_1=1 and α_2 = 10). Column (d) displays the results without clustering (α_1= 0 and α_2 = 1)

Columns (a), and (b) in Figure 2.4 indicate that as the clustering weight is increased, the ecological suitability in each period (thus, the total ecological benefit) decreases because of the decreased number and/or quality of selected sites. Consequently, the total clustering value (sum of distances to reserve centers) also decreases. Comparing column (a) and (c) indicate that placing a higher relative weight on ecological suitability in the objective function increases the total amount of selected ecological suitability and also increases the clustering value. Column (d) indicates that removing the clustering consideration all together will result in a selection of scattered sites. It is clear from these findings that the clustering and price feedback considerations act as opposing forces. Without the clustering consideration the model selects scattered sites that totally eliminate the possibility of paying a higher second period price due to the price premium. The impacts of the weights depend on the dataset and the results demonstrate that the objective function weights should be chosen carefully to achieve the conservation goals and the desired amount of clustering given the budget constraint.

2.5. Concluding Remarks

The reserve site selection problem involves various forms of dynamic aspects that should be considered in a realistic modeling framework for conservation reserve design. Recently Stochastic Dynamic Programming (SDP) and two-period linear optimization have been used to model the dynamic reserve selection problem incorporating uncertainty in site availability. Although the computational complexity of these models may limit their successful application to large real-world data sets, which typically contain hundreds of sites, these studies opened an avenue in the fast growing reserve site selection literature. An important dynamic aspect that has not been addressed in the existing studies relates to changes in market conditions resulting from the increased demand for land due to amenity values, specifically changing land prices depending on the proximity of sites reserved in later time periods to the sites that have been reserved earlier. The two-period model presented here extends the related literature by incorporating location based amenity driven price effects, an economic externality created by spatial requirements in site selection and also by incorporating spatial considerations such as clustering and ecological considerations such as minimum viable populations. The model determines the sites to be purchased in each period while considering the location based amenity driven price effects of reserve development in the first period upon the cost and therefore the site selections in the second period. We then use this model to answer the question "How suboptimal is ignoring amenity driven price effects in reserve design models?" Our simulation findings with randomly generated data demonstrate that not accounting for neighborhood price premiums in reserve design can lead to significant sub-optimality in site selection in terms of the total reserve area (therefore higher costs) depending on the, spread of the price premium, the number of clusters being formed and the second period land market price changes. We test the sensitivity of the model to varying ranges of price premiums. A Monte Carlo simulation with 100 runs involving 100 sites where the site characteristics in each run were randomly generated confirm that this finding is robust and independent of the data set used. The results show that the above findings hold for both small and large price premiums. We present an analysis of the sensitivity of the sub optimality to the spread of price premium by performing a 1000 Monte Carlo simulation runs and show that the sub optimality increases as the spread of the price premium increases. Finally, we relax the assumption that first period prices are homogeneous and allow for the possibility that landowners may have information about the ecological suitability of their land and will charge a higher price for lands with higher ecological value. We show that the general conclusions of the paper are robust to relaxing this assumption. Thus, not accounting for amenity driven price effects can lead to inefficient utilization of scarce conservation resources. The model results presented here show that it is possible to achieve a larger ecological benefit by targeting a single geographical area (or a few areas) in a given time period and not expanding those areas in later time periods. This avoids paying a higher cost for expansions in later periods (if the future expansions are adjacent to previously developed reserve areas) as opposed to spreading the land acquisition over many areas in a given period (which would increase the presence of adjacent site pairs to be purchased). This presents a strong policy recommendation and can be useful in practical reserve design for conservation decision makers.[21]

As discussed in Section 2, development uncertainty has been incorporated into reserve design models using Stochastic Dynamic Programming and two-period integer programming, therefore the results presented above did not incorporate development uncertainty. We simulated uncertainty of land availability and species persistence to test the robustness of the results under uncertainty.[22,23] The results indicate that at low levels of uncertainty, accounting for location based price premiums continue to provide superior results. As the level of uncertainty increases, the advantage in accounting for price effects decreases. This is an expected result since the increasing uncertainty levels decrease the advantage that the forward looking model has over the myopic model.

[21] If the price premium values are low (for example for marginal land) there will not be a significant advantage in accounting for amenity price effects. If the risk of species extinction is high then the focus should be on protecting areas with high risk of species loss.
[22] The method used for the Monte-Carlo simulation allows us to simulate uncertain species survivability.
[23] Refer to Appendix B for a detailed discussion of these results.

The model presented here considers two periods for algebraic simplicity. It can be easily extended to more periods (>2) by defining additional binary variables for each period.[24] A practical alternative is to use the two-period model in a sequential fashion in a 'rolling horizon framework'. Namely, the model can be solved for only two periods in each iteration, after fixing the first period selections a new two-period horizon can be considered starting with the second period of the previous run. This semi-heuristic approach may result in good proxy solutions to the true optimum solution that may be hard to obtain in a single run of the multi-period model.

As previously mentioned, we exogenously specify the value of the location based amenity driven price premium, p_{ak}. This value may vary based on the location and specifics of the conservation area such as the type of ecosystem, access to recreation, etc. One can estimate the value of p_{ak} using non-market valuation techniques such as a hedonic analysis or a choice experiment. In addition to the amenity driven price effect, a large amount of conservation land acquisition may alter land markets, which are not taken into account here. The new land market equilibrium price can be determined if the land demand and supply functions can be estimated. Typically changes in the land market price, which would apply to all land parcels including both the conservation and non-conservation lands, would be small compared to the amenity driven price effect which applies to only 'qualified' parcels.

The model presented in this paper can also be modified to simulate the payment of an option price on future land purchases instead of the price premium. The option price would allow conservation agencies to avoid the loss of ecologically valuable land due to the threat of urban/industrial development.

[24] It should be noted, however, that this will increase the computational complexity of the model mainly because of the increased number of binary variables.

Finally, we note that the linear mixed integer programming model presented here can be programmed and solved with modern off-the-shelf optimization software such as GAMS/CPLEX. This provides improved transparency and convenience to other modelers who work on variations of this problem or with different data sets considering different conservation objectives or site selection criteria. Our computational experience with numerous randomly generated data sets indicate that the model is computationally convenient and can be applied to practical conservation reserve design problems involving several hundred sites.

2.6. References

Ando, A., Camm, J. D., Polasky, S. & Solow, A. 1998. Species distribution, land values and efficient conservation. Science, 2792, 126-2128.

Armsworth, P. R., Daily G. C., Kareiva P., Sanchirico J. N. 2006. Land market feedbacks can undermine biodiversity conservation. Proceedings of the National Academy of Sciences of the United States of America, 103, 5403-5408

Balmford A., Bruner A., Cooper P., Costanza R., Farber, S., Green, R. E., Jenkins, M., Jefferiss, P., Jessamy, V., Madden, J., Munro K., Myers, N., Naeem, S., Paavola J., Rayment, M., Rosendo, S., Roughgarden, J., Trumper K., Turner, R. K. 2002. Economic reasons for conserving wild nature, Science, 297, 950-95.

Cerdeira, J.O., Gaston, K.J. and Pinto, L.S. 2005. Connectivity in priority area selection for conservation. Environmental Modeling and Assessment. 10, 183-192.

Church, R. L. and ReVelle, C. 1974. The maximum covering location problem. Papers in Regional Science Association. 32, 101-118.

Church, R.L., Stoms, D.M., and F.W. Davis. 1996. Reserve selection as a maximal covering location problem. Biological Conservation, 76, 105-112.

Camm, J. D., Polasky, S., Solow, A. and Csuti, B. 1996. A note on optimal algorithms for reserve site selection. Biological Conservation. 78, 353-355.

Costello, C., Polasky, S. 2004. Dynamic reserve site selection. Resource and Energy Economics, 26, 157-174.

Cova, T. J., and Church, R. L. 2000. Contiguity constraints for single-region site search problems. Geographical Analysis, 32, 306–329.

Cowling, R.M., Pressey, R.L., Rouget, M. & Lombard, A.T. 2003. A conservation plan for a global biodiversity hotspot – the Cape Floristic Region, South Africa. Biological Conservation, 112, 191–216.

Fischer, D.T., Church, R.L. 2003. Clustering and compactness in reserve site selection: an extension of the biodiversity management area selection model. Forest Science. 49, 555–565.

Haight, R. G., Snyder, S. 2009. Integer Selection Methods for Reserve Selection and Design. In Moilanen A, Wilson K. A., Possingham, H.P. (Ed), Spatial Conservation Prioritization. Oxford, U.K. Oxford University Press. 43-56.

Hanski, I., Simberloff, D. 1997 The metapopulation approach. In: Metapopulation Biology: Ecology, Genetics, and Evolution (eds.Hanski IA, Gilpin ME), pp. 5–26. Academic Press, Inc. San Diego, Harrison, S., 1994. Metapopulations and conservation. In: Edwards, P.J., May, R.M., Webb, N.R. (Eds.), Large-Scale Ecology and Conservation Biology. Blackwell Scientific, Oxford, pp. 111–128.

Harpankar, K. 2006. Reserve Selection in the presence of Economic Feedback Effects http://ageconsearch.umn.edu/bitstream/21177/1/sp06ha02.pdf

Irwin, E.G., 2002. The effects of open space on residential property values. Land Economics, 78 (4), 465–480.

James, A. N., K. J. Gaston, and A. Balmford. 1999. Balancing the earth's accounts. Nature 401, 323–324.

Kirkpatrick, J. B. 1983. An iterative method for establishing priorities for the selection of nature reserves: An example from Tasmania. Biological Conservation, 25(2), 127-134.

Margules, C.R., Pressey, R.L. 2000. Systematic conservation planning. Nature. 405: 243-53.

McConnell, V., Walls, M. 2005. The Value of Open Space: Evidence from Studies of Nonmarket Benefits. Resources for the Future, Washington, D.C

McDonald-Madden, E., Bode M., Game, E. T., Grantham, H., Possingham H. P. 2008. The need for speed: informed land acquisitions for conservation in a dynamic property market. Ecology Letters, 11, 1169-1177.

Meir E., Andelman S., Possingham H. P. 2004. Does conservation planning matter in a dynamic and uncertain world? Ecology Letters, 7: 615-622.

Moilanen A., Cabeza M. 2002. Single-species dynamic site selection. Ecological Applications, 12: 913 - 926.

Moilanen, A., Ball I. 2009. Heuristic and Approximate Optimization Methods for Spatial Conservation Prioritization. In Moilanen A, Wilson K. A., Possingham, H.P. (Ed), Spatial Conservation Prioritization. Oxford, U.K. Oxford University Press. 58 - 69.

Naidoo R., Balmford, A., Ferraro P. J., Polasky S. 2006,. Integrating economic costs into conservation planning. Trends in Ecology Evolution, 21: 681 – 687.

Neumann, B. C., Boyle, K. J., & Bell, K. P. 2009. Property price effects of a national wildlife refuge: Great meadows national wildlife refuge in Massachusetts. Land use Policy, 26, 1011-1019.

Newburn, D., Reed, S., Berck P., Merenlender, A. 2006. Habitat and open space at risk of land-use conversion: Targeting strategies for land conservation. American Journal of Agricultural Economics, 88, 28 - 42.

Newburn D., Reed S., Berck P., Merenlender A. 2005. Economics and land-use change in prioritizing private land conservation. Conservation Biology, 19, 1411 - 1420.

Önal, H., Briers R. A. 2003. Selection of a Minimum-Boundary Reserve Network Using Integer Programming. Proceedings of the Royal Society of London: Biological Sciences 270, 1487-149

Önal, H. 2004. First-best, second-best, and heuristic solutions in conservation reserve site selection. Biological Conservation 115: 55–62.

Önal H., Briers R. A., 2006. Optimal selection of a connected reserve network. Operations Research 54, 379-388.

Önal, H. and Y. Wang. 2008. A Graph Theory Approach for Designing Conservation Reserve Networks with Minimal Fragmentation. Networks 52, 142-152.

Possingham, H., I. Ball, and Andelman, S. 2000. Mathematical methods for identifying representative reserve networks. In Quantitative Methods for Conservation Biology (ed. S. Ferson & M. Burgman), pp. 291-306. Springer, New York

Possingham, H.P. & Wilson, K.A. 2005. Biodiversity – turning up the heat on hotspots. Nature, 436, 919–920.

Possingham, H., Wilson, K. A., Andelman, S. J. and Vynne, C. H. 2006. Protected areas: Goals, limitations, and design. In Martha J. Groom, Gary K. Meffe and C. Ronald Carroll (Ed.), Principles of Conservation Biology 3rd ed. ed. (pp. 507-549) Sunderland, Massachusetts, U.S.: Sinauer Associates.

Polasky S. 2006.You can't always get what you want: Conservation planning with feedback effects. PNAS 103:5245-5246.

Rodrigues, A.S.L. and K.J. Gaston. 2002. Optimisation in reserve selection procedures - why not? Biological Conservation 107, 123-129.

Sabbadin, R., Spring, D., Rabier, C.E. 2007. Dynamic reserve site selection under contagion risk of deforestation. Ecological. Modeling. 201, 75–81.

Snyder S., Haight R. G., ReVelle C. S. 2004. A scenario optimization model for dynamic reserve site selection. Environmental Modeling Assessment 9: 179 - 187.

Strange N., Thorsen B. J., Bladt J. 2006. Optimal reserve selection in a dynamic world. Biological Conservation 131, 33 - 41.

Tajibaeva, L., Haight, R. G. and Polasky. S. 2008. A Discrete-Space Urban Model with Environmental Amenities. Resource and Energy Economics 30 (2): 170–196.

Toregas C. and ReVelle C. 1973. Binary logic solutions to a class of location problems, Geographical Analysis, 5, 145–155.

Underhill, L.G. 1994. Optimal and suboptimal reserve selection algorithms. Biological.

Conservation, 70, 85-87.

Williams, J. C. 2002. A zero-one programming model for contiguous land acquisition. Geographical Analysis 34, 330-349.

Williams, J. C. and ReVelle,C.S. 1996. A 0-1 programming approach to delineating protected reserves. Environment and Planning B 23, 607-622.

Williams, J. C. and ReVelle,C.S. 1998. Reserve assemblage of critical areas: A zero-one programming approach. European Journal of Operational Research 104, 497-

509.Williams J. C., ReVelle C. S., Levin S. A. 2005. Spatial attributes and reserve design models: A review. Environmental Modeling Assessment, 10(3), 163-181.

Wu, J. 2001. Environmental Amenities and the Spatial Pattern of Urban Sprawl. American Journal of Agricultural Economics 83: 691-697.

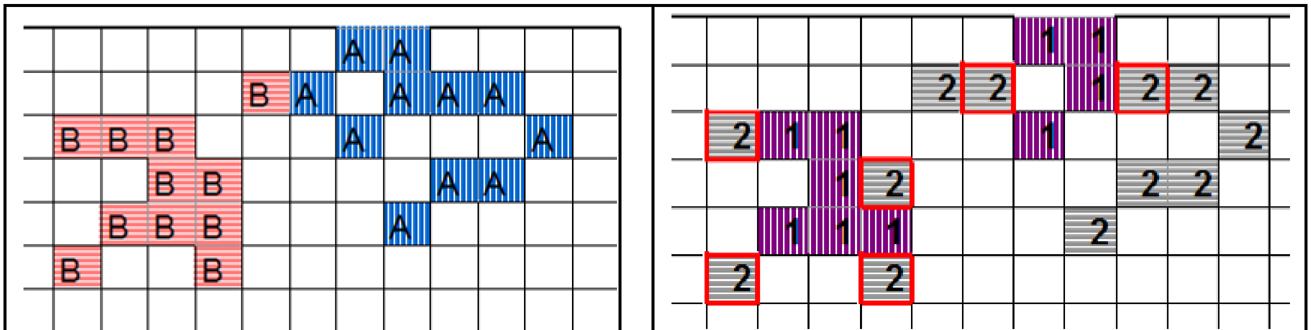
Wu, J., Adams R. M., and Plantinga. A. J. 2004. Amenities in an Urban Equilibrium Model: Residential Development in Portland, Oregon. Land Economics, 80(1): 19-32.

Wu, J. & Irwin E.G.. 2008. Optimal land development with endogenous environmental amenities. American Journal of Agricultural Economics. 90: 232–248.

2.7. Tables and Figures

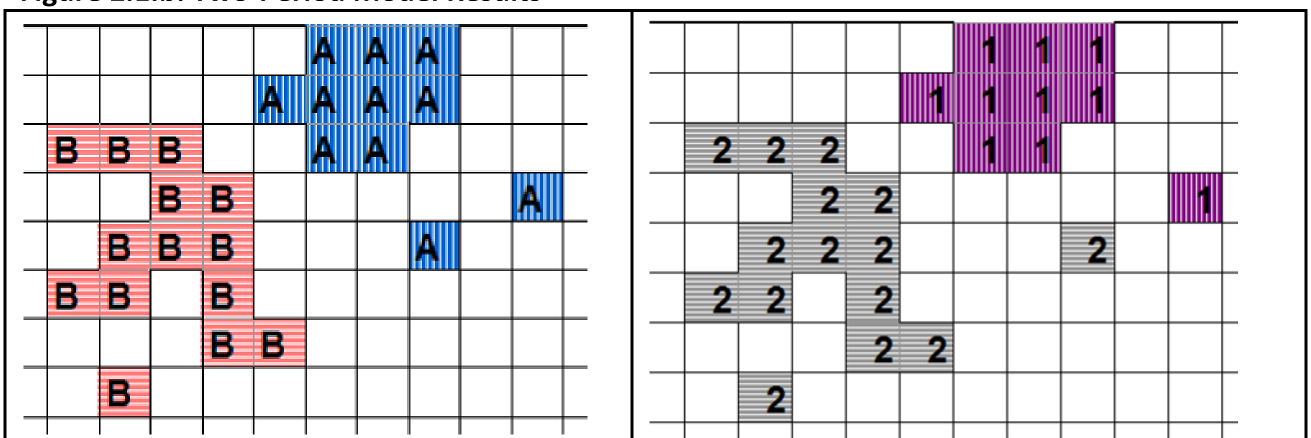
Results for Two Reserves

Figure 2.1.a: Iterated One-Period Model Results[25]



The two reserves identified by A and B	The period of selection is identified by 1 and 2

Figure 2.1.b: Two-Period Model Results[16]



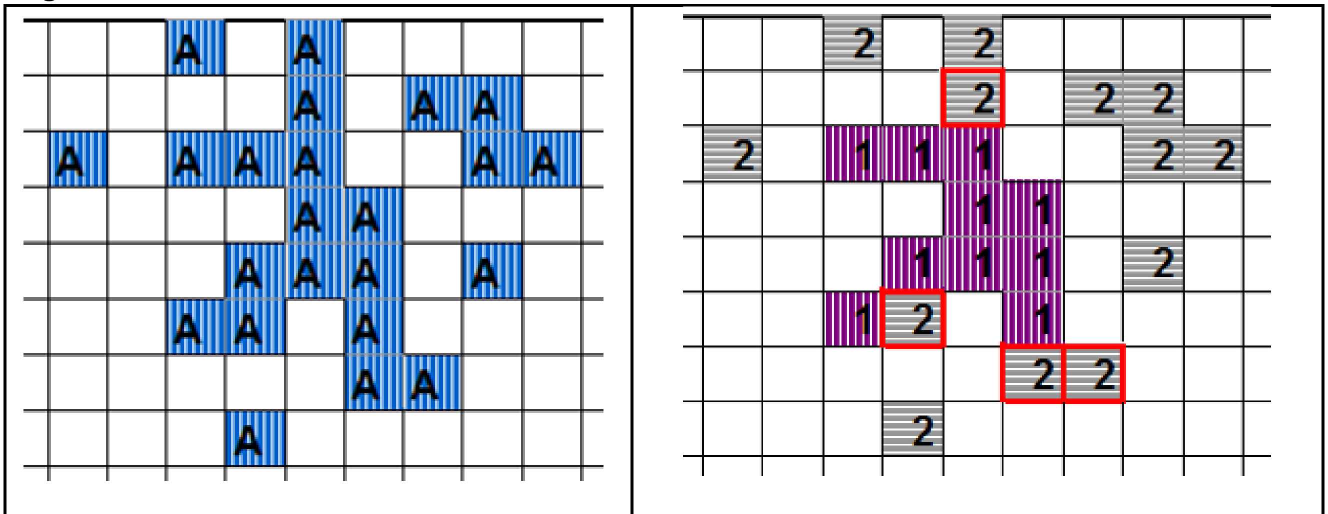
The two reserves identified by A and B	The period of selection is identified by 1 and 2

Legend

[25] Only the area selected by the model is shown in the figure to better emphasize the selections.

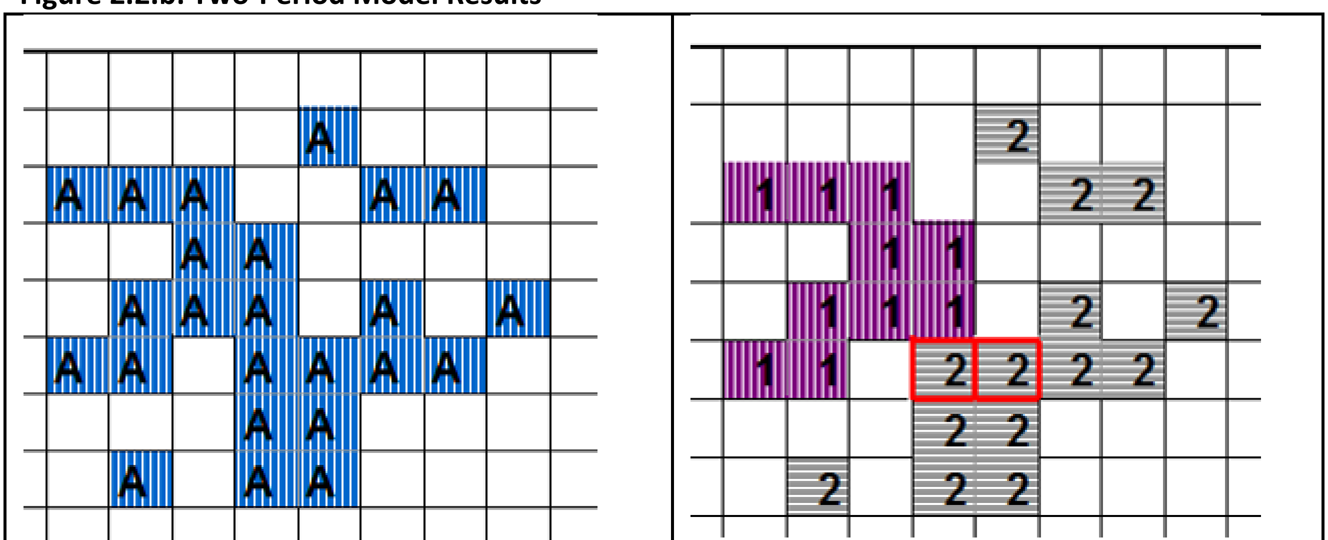
Results for One Reserve

Figure 2.2.a: Iterated One-Period Model Results[26]



The reserve is identified by A	The period of selection is identified by 1 and 2

Figure 2.2.b: Two-Period Model Results[17]



The reserve is identified by A	The period of selection is identified by 1 and 2

Legend

[26] Only the area selected by the model is shown in the figure to better emphasize the selections.

Figure 2.3: Graph of Difference in Habitat Suitability vs Second Period Price Premium

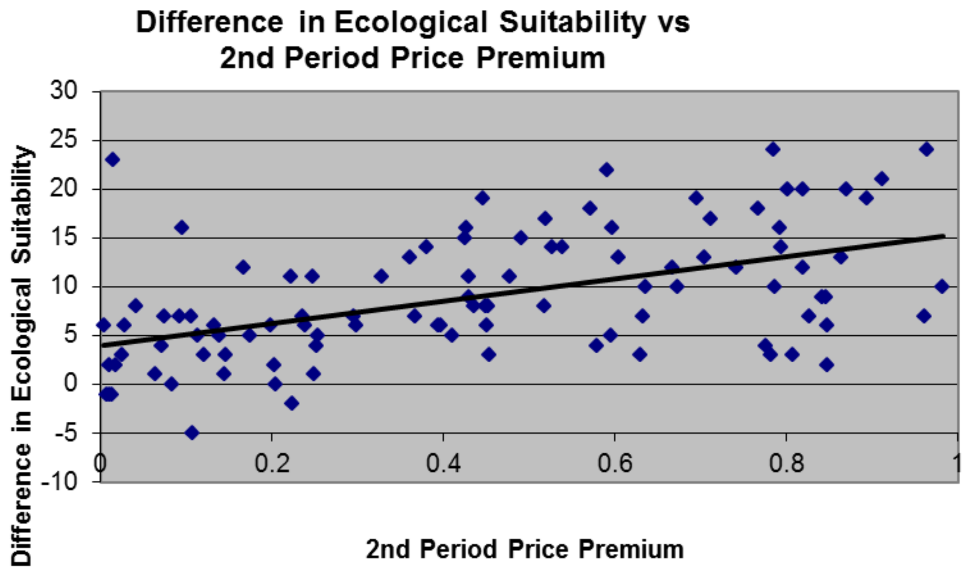
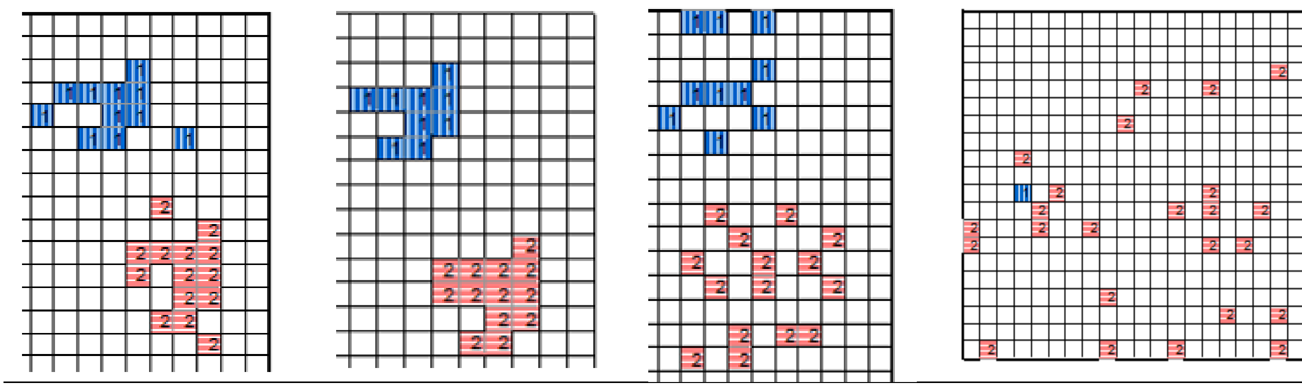


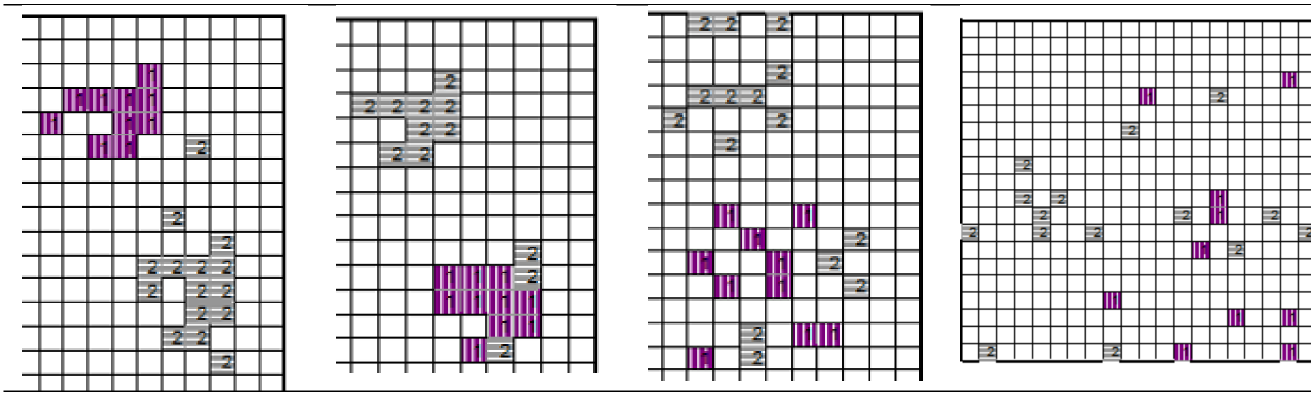
Figure 2.4. Sensitivity Analysis of the Objective Function Weights[27]

Legend — 1 Cluster 1; 2 Cluster 2; 1 Period 1 Selection; 2 Period 2 selection

α1 = 1, α2 = 1	α1 = 2, α2 = 1	α1 = 1, α2 = 10	α1 = 0, α2 = 1, α3 = 1



Reserve Selections	Reserve Selections	Reserve Selections	Reserve Selections



Selected Time Period	Selected Time Period	Selected Time Period	Selected Time Period
1st period selections = 10 2nd period selections = 15 1st period coverage = 47 2nd period coverage = 69 Clustering value = 42.15	1st period selections = 10 2nd period selections = 12 1st period coverage = 42 2nd period coverage = 69 Clustering value = 30.67	1st period selections = 10 2nd period selections = 15 1st period coverage = 50 2nd period coverage = 75 Clustering value = 59.19	1st period selections = 10 2nd period selections = 15 1st period coverage = 50 2nd period coverage = 75 Clustering value = 192.40
(a)	(b)	(c)	(d)

[27] Only the area selected by the model is shown in the figure to better emphasize the selections.

Figure 2.5: Difference in ecological suitability vs price premium with changing levels of uncertainty

(Based on 500 Monte Carlo simulations)

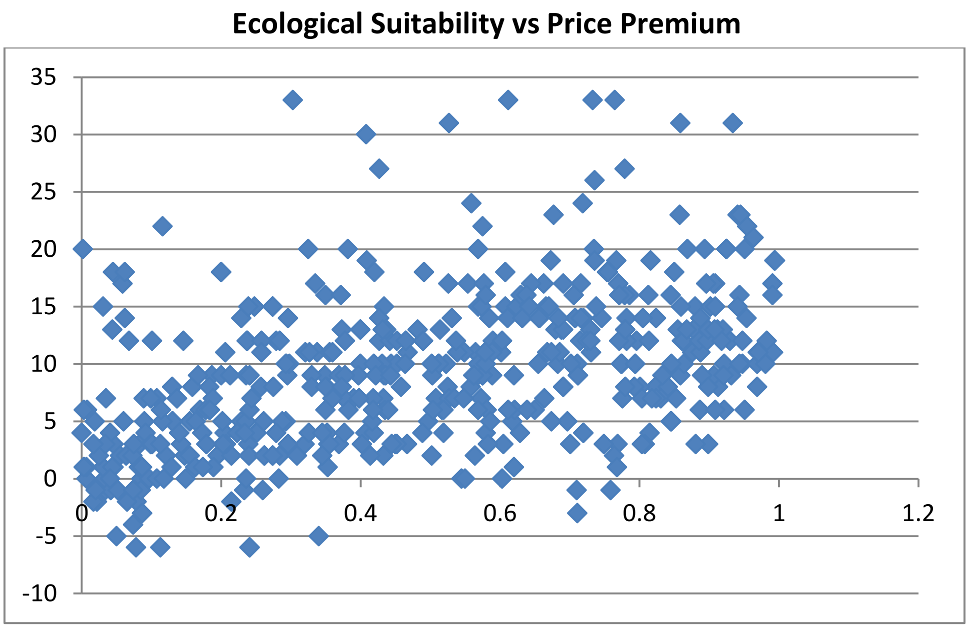


Figure 2.5.a: 10% uncertainty that second period sites will not have a conservation value

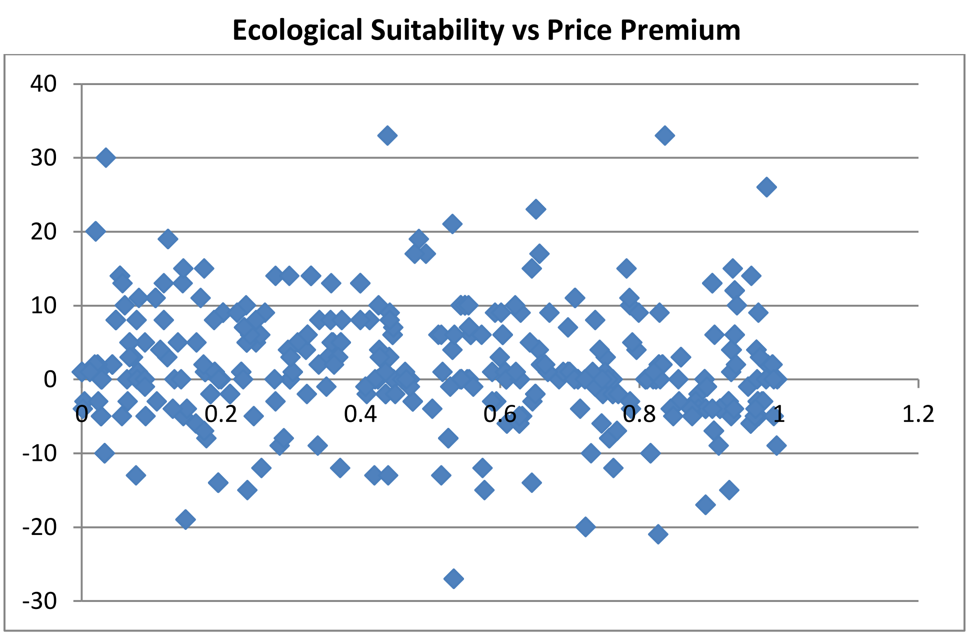


Figure 2.5.a: 10% uncertainty that second period sites will not have a conservation value

Table 2.1: Monte Carlo Simulation Results for Comparison of the Two-Period Model and the Iterated One-Period Model (Based on 100 Monte Carlo simulations)

	Price Premium	Total Cost	Total sites selected	Ecological Suitability in period one	Total Ecological Suitability	Clustering value	Ecological Suitability per currency unit
2-Period							
Mean	0.442	29.470	25.870	42.530	111.180	45.440	3.773
STD	0.294	0.299	0.367	2.761	5.082	3.298	0.178
Iterated 1P							
Mean	0.442	29.277	23.550	47.650	102.140	43.842	3.490
STD	0.294	1.199	1.672	1.540	8.220	5.551	0.255
Analysis of the difference between the 2-period and iterated 1-period models							
Mean (percentage change_)			2.313 (9.82%)		9.040 (8.85%)		0.282 (8.08%)
STD			1.569		6.50		0.210
T-Stat			14.8461		13.9627		13.5651
P-Value 2Period – 1Period			0.000 > 0		0.0000 > 0		0.0000 >0

Table 2.2: Percentage improvement in ecological suitability of the two-period model over the iterated one-period model as a function of the spread of the price premium
(Based on 1000 Monte-Carlo simulations)

Price Premium	Percentage Improvement in Ecological Suitability
0%-10% (85 runs)	1.78%
0%-20% (206 Runs)	4.24%
0%-30% (319 runs)	4.75%
0%-40% (423 runs)	5.64%
0%-50% (512 runs)	6.58%
40%-50% (89 runs)	11.04%

Table 2.3: Monte Carlo Simulation Results for Comparison of the Two-Period Model and the Iterated One-Period Model When First Period Prices are Dependent on Ecological Land Suitability
(Based on 1000 Monte Carlo simulations)

	Price Premium	Total sites selected	Ecological Suitability in period one	Total Ecological Suitability	Clustering value
2-Period					
Mean	0.505	23.968	39.383	103,908	40.243
STD	0.298	0.270	2.273	4.232	2.475
Iterated 1P					
Mean	0.505	21.916	43.302	96.038	43.302
STD	0.298	1.389	1.228	6.580	1.228
Analysis of the difference between the 2-period and iterated 1-period models					
Mean (percentage change_)		2.052 (9.363%)		7.87 (8.194%)	
STD		1.371		5.661	

Table 2.4: Analysis of the difference between the two-period and iterated one-period model when uncertainty increases
(Based on 500 Monte Carlo simulations)

	Total Ecological Suitability	Ecological Suitability per Currency Unit
Analysis of the difference for 10% uncertainty		
Mean	9.224	0.281869
STD	6.801054	0.213173
Analysis of the difference for 50% uncertainty		
Mean	1.582	-0.02451
STD	8.373022	0.230559

3. Economic valuation of ecosystem attributes for optimal ecosystem restoration design

Sophisticated non-market valuation techniques have been developed by economists to estimate the value to society of goods not sold in the marketplace such as environmental quality and mortality risk reduction. In environmental economics, these value estimates have been used primarily as critical inputs to cost-benefit analyses and to estimate damages for which firms can be held liable after events such as oil spills. In this paper, we demonstrate how a relatively new tool in the valuation toolkit – choice experiment survey methods – can also be used for another important use: guiding complex decisions about how best to carry out and manage ecosystem restoration projects. We use a choice experiment survey of Illinois residents to estimate willingness to pay (WTP) for different attributes of restored grassland ecosystems: species richness, bird population density, presence of endangered species, and presence of wildflowers. The results reveal several interesting patterns of consumer preferences and choice. First, we find that the presence of nearby existing grasslands actually increases a respondent's WTP for restoring a new grassland; this result is counter to what would be expected from neoclassical economics and can possibly be explained by endogenous preferences. Second, we find that respondents treat the conservation success measures (species richness, population density and endangered species) as substitutes for each other; the marginal value of one measure is lower when the levels of the other two measures are high, and contours of total value are concave in pairs of attributes rather than convex. This latter finding implies that value-maximizing grassland design might well display corner solutions in which restoration ecologists maximize the value of a single conservation goal – producing endangered-species havens or duck factories – rather than aiming for balanced bundles of these attributes. We finally analyze the impact of including attribute interaction terms on the total willingness to pay (TWTP) and on the TWTP maximizing set of conservation success variables.

3.1. Introduction

Non-market valuation techniques have been developed by economists to estimate the value to society of goods not sold in the marketplace such as environmental quality and mortality risk reduction. In environmental economics, these value estimates have been used primarily as critical inputs to cost-benefit analyses and to estimate damages for which firms can be held liable after events such as oil spills. In this paper, we demonstrate how a tool in the environmental-economics valuation toolkit – choice experiment survey methods – can also be used for another important use: guiding complex decisions about how best to carry out and manage ecosystem restoration projects. We do this by estimating consumer preferences over multiple conservation attributes of restored ecosystems.

Large scale conversion of many natural habitats has put pressure on rare and endangered species and decreased the flows of many ecosystem services. In response, conservation organizations seek to protect and restore land with high conservation and biodiversity values; this has led to much research on optimal protected area planning (e.g. Ando et al. 1998; Margules and Pressey 2000; Primack 1993) and restoration (Loomis et al. 2000; Meyerhoff and Dehnhardt 2007; Milon and Scrogin 2006). Most of that research uses production-side factors – the locations of endangered species, the cost of land, the threat posed to natural areas by development - to guide decisions about where to locate dedicated natural areas and what features those areas should have. However, Ando and Shah (2010) show that conservation activity can yield higher social benefits if decision makers consider the preferences of people when they plan their network of natural areas.

Two features of consumer preferences are important for deciding how best to invest social resources in restoration projects. First, the structure of preferences over multiple attributes of a given restoration project affects the nature of the value-maximizing bundle of attributes. Most existing non-market valuation research that identify values for restoration use contingent valuation (CV), which does not allow relationships in the values of multiple attributes to be analyzed. The studies of restoration values that use choice experiment (CE) surveys (Birol et al. 2006; Carlsson et al. 2003; Christie et al. 2006) do not use attribute interaction terms; the standard econometric specification of that research implicitly assumes consumers have linear indifference curves between pairs of attributes that comprise the good. This paper uses CE valuation techniques to estimate the values of and the nature of substitutability between multiple facets of a restored ecosystem by including interaction terms between attributes. This allows the estimation of how the marginal value of any one measure of conservation success - species richness, population density, and the presence of endangered species - is affected by the levels of the other two.

Second, optimal positioning of a restored area in the landscape depends on how the value people derive from an area varies with proximity and with features of the landscape around it. Competing economic theories yield diverse predictions about how the existing quantity of an environmental public good (an existing natural area) affects the WTP for providing more of that good (restoring more of that ecosystem). Neoclassical economic consumer theory predicts that marginal willingness to pay for an increase in a public good will be lower for consumers who already have access to a relatively large quantity of that good. On the other hand, endogenous preferences or experience can lead to the opposite effect (Bowles 1998; Cameron and Englin 1997; Gowdy 2004; Zizzo 2003). We evaluate these competing theories by analyzing how the willingness to pay to restore a new grassland is affected by the presence of grassland areas nearby. We also estimate how consumer WTP for a restored area varies with how far they live from it, contributing more evidence to the growing body of work on this subject (e.g. Bateman et al. 2006)

We carry out our research on the structure of consumer preferences over restoration projects in a setting that has been neglected by the valuation literature: grassland ecosystems. Though there have been many CV (and more recently CE) studies estimating the values of conserving and restoring ecosystems such as wetlands and forests, economic valuation efforts have not been focused on estimating the social value of grassland ecosystems. Massive conversion of grassland in North America to urban and agricultural use has stressed wildlife and cut ecosystem service provision in large swaths of the continent. This problem can be addressed with grassland restoration activities, but such projects are costly and require difficult and seemingly arbitrary choices to be made about the exact nature of the grasslands created. The restoration ecologists who carry out grassland restoration have no guidance from the economic valuation literature about the preferences people have over the characteristics of restored grasslands. In this paper we meet that need for knowledge by using a choice experiment survey of Illinois residents to analyze willingness to pay (WTP) for grassland habitat restoration.

We find that that species richness, population density, presence of endangered species, presence of wildflowers, and distance from an individual’s home are all significant factors that affect consumers’ WTP to restore an endangered ecosystem. This challenges the common practice of using just one measure, such as species richness, as a stand-alone indicator of conservation success. We also find that respondents with existing grasslands nearby have a higher WTP for restoring a new grassland; this result is counter to what would be expected from neoclassical economics and can possibly be explained by endogenous preferences. Finally, the marginal value respondents place on any one conservation goal (species richness, population density and endangered species) is lower if the levels of the other two conservation goals are high. This finding implies that respondents have convex total willingness to pay contours, as opposed to linear or concave. Thus, the bundle of conservation attributes that maximize TWTP has positive levels for only one of the conservation success measures (e.g. a corner solution where only the number of endangered species has a positive value). This result changes only if physical factors constraint the levels of conservation success values.

3.2. Literature Review

There is a fairly extensive literature on using non-market valuation to obtain values for restoring ecosystems. Examples include studies of; the values for restoring an impaired river basic using a CV study by Loomis et al. (2000); the total economic value of restoring ecosystem services in Ejina region in a CV study by Zhongmin et al. (2003); the benefits of woodland restoration in native forests in UK in a CV study by Macmillan and Duff (1998);the benefits of riparian wetland restoration focused on the river Elbe in Germany in a CV study by Meyerhoff and Dehnhardt (2007); the factors that lead to community participation in mangrove restoration in India in a CV study by Stone et al. (2008); the preferences for river restoration in a combined CE and CV study by Weber and Stewart(2009); the socioeconomic factors and psychometric measures that effect wetland restoration in latent class choice model by Milon and Scrogin (2006); the WTP for the conversion of cropland to forest and grassland program in

North West China in a CE survey by Wang et al. (2007). Much of this literature uses CV studies and therefore is unable to identify the structure of consumer preferences between various facets of ecosystem services.

A single measure of conservation success, such as species richness or the number of endangered species has been used in many ecological and protected areas selection studies (Ando et al. 1998; Cabeza et al. 2004; Csuti et al. 1997; Haight et al. 2000; Kharouba and Kerr 2010; Possingham et al. 2010; Pressey et al. 2007; Önal 2004; Önal and Briers 2005) . Studies such as Loomis and Larson (1994) and Fletcher and Koford (2002) demonstrate that wildlife population density is also an important variable affecting the public's WTP for habitats. Further, in terms of maximizing benefits from conservation and restoration it is important to understand how each of these conservation success measures influences the WTP and how they are related to each other (i.e. do respondents treat the conservation success measure as substitutes or complements). Christie et al. (2006) study public preferences and WTP for biodiversity in general and Meyerhoff et al. (2009) find that the species richness is a significant attributes that determines the WTP for forest conservation. However, neither of the above studies includes wildlife population density as an attribute, making it difficult to understand the role that each of these attributes play in determining the WTP for restoration projects.

Much of the non-market valuation literature on conservation and restoration has focused on wetland preservation and restoration (Boyer and Polasky 2004; Heimlich et al. 1998; Woodward and Wui 2001), forest preservation and restoration (Adger et al. 1995; Baarsma 2003; Lehtonen et al. 2003), the protection of individual endangered bird species (Bowles 1998; Loomis and Ekstrand 1997) or recreation and hunting (Boxall et al. 1996; Hanley et al. 2002;

Horne and Petajisto 2003; Roe et al. 1996). To our knowledge, no economic valuation study to date has analyzed preferences for grassland ecosystems. The closest study is a paper by Earnhart (2006) that estimates the aesthetic benefits generated by open space adjacent to residential locations, where the open space is denoted by prairie, but this paper does not analyze the preferences for characteristics of grassland ecosystems nor the WTP to restore grasslands.

Identifying whether existing and new environmental public goods act as substitutes or complements, especially with regard to restoration of ecosystems and natural habitats, will enable conservation organizations to better target conservation efforts. Carson et al. (2001) discuss how public goods will act as substitutes and the WTP will decrease as more of the public good is provided. This follows from a neoclassical consumer framework that the demand function is downward sloping. At the same time, the presence of an environmental public good can lead to learning, experience and appreciation such that agents who currently experience high levels of the public good may have a higher willingness to pay for more of that good (Cameron and Englin 1997; O'Hara and Stagl 2002). This can be explained using endogenous preference theory, which argues that consumers who are familiar with a good may be willing to pay more than consumers who are unfamiliar with the good (Bowles 1998; Gowdy 2004; O'Hara and Stagl 2002; Zizzo 2003). Cameron and Englin (1997) show that experience can lead to higher resource values using a CV study of WTP for trout fishing. They find that experience, measured by the number of years in which the respondent has gone fishing, has a significant positive impact on the WTP. A related theory of planned behavior proposed by Ajzen (1991) states that WTP is expected to increase with a more favorable attitude toward paying for a good (Liebe et al. 2011). Therefore if a favorable attitude towards grasslands can arise from opportunities to experience existing nearby grasslands, respondents with grasslands nearby will have a higher WTP to restore a new grassland.

3.3. Background on Grassland Ecosystems

Grasslands are open land areas where grasses and various species of wildflowers are the main vegetation. In North America there are three main types of grassland ecosystems. The short-grass ecosystem predominantly occurs on the western and more arid side of the Great Plains. The mixed-grass ecosystem is located farther to the east. The tall-grass ecosystem occurs on the eastern side of the Great Plains. Tall grass can grow up to 4-6 feet. Figure 3.1 presents the distribution of grassland ecosystems in North America (O'Hanlon 2009).

The loss of grassland in North America is attributed to deforestation in the eastern United States, fragmentation and replacement of prairie vegetation with a modern agricultural landscape, and large-scale deterioration of western U.S. rangelands (Brennan and Kuvlesky Jr 2005). The loss of grassland ecosystems in most areas of North America has exceeded 80% since the mid-1800s (Brennan and Kuvlesky Jr 2005; Knopf 1994; Noss et al. 1995). As depicted in Figure 3.2.a and Figure 3.2.b, Illinois has lost 99.9% of its original prairie since the early 1800s, and currently has 424 state and 24 federally listed threatened and endangered species within its boundaries (Illinois Department of Natural Resources 2010).

Samson and Knopf (1994) state that North America prairies are a major priority in biodiversity conservation. The loss of grasslands has contributed to a widespread and ongoing decline of bird populations that have affinities for grass-land and grass-shrub habitats (Askins et al. 2002; Brennan and Kuvlesky Jr 2005; Vickery and Herkert 1999). An analysis of the Breeding

Bird Survey routes between 1966 and 2002 showed that only 3 of 28 species of grassland specialists increased significantly, while 17 species decreased significantly (Sauer et al. 2003). During the 25-year period ending in 1984, grassland songbirds in Illinois declined by 75% - 95% (Heaton 2000). Vickery and Herkert (1999) state that given the extent of the decrease in grassland habitat, widespread restoration of grasslands throughout the U.S. is the most effective approach to restoring bird populations.

In an effort to address these growing concerns, ecologists and conservation biologists are engaged in restoring grassland habitats to protect endangered flora and fauna. Restoration ecologists have the ability to structure the restoration to emphasize certain attributes in restored ecosystem but such restoration projects are currently informed by knowledge only from the physical, biological, and ecological sciences (Fletcher and Koford 2002; Hatch et al. 1999; Howe and Brown 1999; Martin et al. 2005; Martin and Wilsey 2006). Restoration planners must make choices about exactly how and where to carry out ecological restoration, and those choices entail physical tradeoffs between the exact types of restored ecosystems that result, the kinds of animals and plants that inhabit the restored areas, the variety of species that are supported by the project, the density of wildlife populations that will be present, and the types of management tools used to maintain these areas. These choices must currently be made in an absence of knowledge about public preferences regarding the characteristics of grassland restoration projects.

3.4. Methodology

3.4.1 Choice Experiment Surveys

CE surveys are being used by economists to elicit public preferences for environmental goods and policies that are typically not related to existing markets (Boxall et al. 1996; Louviere et al. 2000). CE surveys are based on Lancaster's (1966)consumer theory that consumers obtain utility from the characteristics of goods rather than the good itself. Therefore, CEs can be considered the equivalent of hedonic analysis for stated preference valuation methods. Though CE surveys are more complex to analyze and implement than contingent valuation studies, they allow the researcher to a detailed understanding of the respondents' preferences for the policy or scenario being analyzed. Unlike CV surveys, CE surveys allow the calculation of part worth utilities for attributes, which is necessary to answer the research questions in this paper. Hanley et al. (2001) and Hoyos (2010) provide reviews of the choice experiment methodology.

In a typical CE survey, the respondent repeatedly chooses the best option from several hypothetical choices that have varying values for important attributes. Choice experiment surveys require the use of experiment design techniques to identify a combination of attributes and levels to create the profiles appearing on each survey.

3.4.2 Survey Instrument

The survey for this research will present respondents with opportunities to express preferences over pairs of hypothetical restored grasslands that have the following attributes: species richness, wildlife population density, number of endangered species, frequency of prescribed burning, prevalence of wildflowers, distance to the site from the respondent's house, and cost. Some attributes were motivated by our intent to explore preferences regarding common measures of conservation success. The exact list of grassland attributes was refined after studying the grassland restoration literature and nonmarket valuation literature.

A CV study on preferences for urban green space in Montpellier, France and a CV study on preference for protecting or restoring native bird populations in Waikato, New Zealand find that providing information about the presence of birds significantly effects the WTP. Therefore we include information about bird species in the survey. A study by Gourlay and Slee (1998) on public preferences for landscape features find that wildflowers were one of the features most frequently valued 'highly' or 'very highly'. Since wildflowers are an integral part of the grassland ecosystems we include the area covered by wildflowers as an attribute. Historically, fire has been a natural component of grassland ecosystems and many grassland restoration efforts require management by fire to prevent woody succession and to eliminate invasive species (Copeland et al. 2002; Howe 1995; Schramm 1990; Vogl 1979). At the same time smoke and ash from prescribed burns can be hazardous to motorists and become a problem for local residents. Therefore we include the use of prescribed burns as an attribute in the survey.

Once an initial list of attributes was developed we conducted informal focus groups with potential survey respondents and discussed the survey with ecologists and land managers at grasslands. Formal pre-tests of the survey were conducted at the University of Illinois. The final survey instrument contains background information about grasslands, a description of the attributes and the levels, 7 sets of binary choice question sets, and a small demographic questionnaire. Appendix C contains an example of one choice question. For each of the binary choice sets the respondents choose between the two given alternatives and the status quo option. The choices will contain different features of the restored area and specific values for these features. The demographic questionnaire has two questions regarding the presence of nearby grasslands and non-grassland nature areas. The answers to these questions are used to test whether the presence of nearby grasslands and nature areas has a significant impact on the WTP to provide a new grassland.

The survey was mailed to a random sample of 2000 addresses in Illinois, stratified according to population density. The addresses were obtained from the Survey Research Lab at the University of Illinois. The addresses were oversampled from two counties with existing grasslands and two counties without existing grasslands. One dollar bills were included half of the surveys to increase the survey response rate.

3.4.3 Empirical Design

Given that each choice profile is a binary choice question with a status quo option, a full factorial survey design would include 3^6*3^6*6*6= 19131876 possible profiles. Clearly, conducting a survey with this many profiles is impractical. Therefore, we follow standard practice in the choice modeling literature (Adamowicz et al. 1997; Adamowicz et al. 1998; Louviere et al. 2000) and create an efficient experiment design that will allow both main effects and interaction effects to be estimated. Given that we are interested in studying the interaction effects between different indicators of conservation success the design incorporates pairwise interactions between species richness, population density and number of endangered species. The design for the 7 attributes is presented in Appendix C.[28] The design achieves a 99.57% D-efficiency and can be implemented with 54 choice profiles[29]. The first column in Appendix C

[28] The experiment design was conducted using the SAS experiment design ((Kuhfeld, 2010)).
[29] D-efficiency is the most common criterion for evaluating linear designs. D-efficiency minimizes the generalized variance of the parameter estimates given by D = det [V(X,β)1/k] where V(X, β) is the variance-covariance matrix

identifies the profile set and the last 7 columns identify the levels of each attribute that will appear on the survey. We created a block design where the 54 choice sets were separated into blocks of 6 choice profiles, giving 9 unique surveys with 6 questions each. Carlsson et al. (2010), test for learning and ordering effects in CE surveys and show that dropping the first choice question can decrease the error variance of estimates. Therefore, we add an additional choice question before the six choice questions and drop the first choice question when conducting the analyses to account for possible learning effects. In order to account for possible ordering effects we reversed the order of the questions in half the surveys and obtained 18 unique versions of the survey.

3.4.4 Model and Estimation

CE surveys are based on random utility theory (RUM) in which the utility gained by person *q* from alternative *i* in choice situation *t* is made up of a systematic or deterministic component (*V*) and a random, unobservable component (ε) (Hensher and Greene 2003; Hensher et al. 2005; Rolfe et al. 2000).

$$U_{qit} = V_{qit} + \varepsilon_{qit} \tag{1}$$

Following Rolfe et al. (2000) and Hensher et al. (2005) the systematic component in (1) can be separated by the characteristics of the alternative *i* (X_{in}) and the characteristics of the individual *q* as below.

$$U_{qit} = V(X_{qit}, Y_{qit}) + \varepsilon_{qit} \tag{2}$$

An individual will choose alternative *i* over alternative *j* in choice set *t* if and only if $U_{qit} > U_{qjt}$.

---

and k is the number of parameters ((Kuhfeld 2010; Vermeulen et al. 2008)). (Huber and Zwerina 1996)identify four criteria, orthogonality, level balance, minimum overlap and utility balance, which are required for a D-efficient experiment design ((Kuhfeld 2010)).

Thus, the probability that person *q* will choose alternative *i* over alternative *j* is given by:

$$P_{ij} = \mathrm{Prob}(V_{iq} + \varepsilon_{iq} > V_{jq} + \varepsilon_{jq}; \forall j \in C \, and \; j \neq i) \tag{3}$$

where *C* is the complete set of all possible sets from which the individual can choose. If the error term ε is assumed to be IIA and Gumbel-distributed the choice probabilities can be analyzed using a standard multinomial logit model and the probability of choosing alternative *i* can be calculated by the following equation where μ is a scaling parameter (Hensher et al. 2005; Mcfadden 1974; Rolfe et al. 2000):

$$\mathrm{Prob}_{qit} = \frac{\exp(\mu v_{qit})}{\sum_{j \in C} \exp(\mu v_{qjt})}. \tag{4}$$

The standard multinomial logit model generates results in a conditional indirect utility function of the form,

$$V_{iq} = \mathrm{ASC}_i + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_a Y_1 + \beta_b Y_2 + ... + \beta_k Y_n \tag{5}$$

where ASC_i is an optional alternative-specific constant which can capture the influence on choice of unobserved attributes relative to specific alternatives (Carlsson et al. 2003; Hensher et al. 2005).[30] The β's represent the coefficients on the vector of attributes and individual characteristics. A willingness-to-pay compensating variation welfare measure can be obtained from the above estimates as

$$WTP = \beta_{\cos t}^{-1} \ln \left[\frac{\sum_i \exp(v_i^1)}{\sum_i \exp(v_i^0)} \right] \tag{6}$$

[30] For the empirical specification we do not include an ASC term since the specific alternatives are generic and unlabeled.

where $\beta_{\cos t}^{-1}$ is the marginal utility of income ((Hanley et al. 2002)).[31] The part-worth marginal value of a single attribute can be represented as

$$WTP_k = -\beta_k / \beta_{\cos t}. \tag{7}$$

Though the standard multinomial logit model has been used in many valuation studies of environmental goods, it assumes that the respondents are homogeneous with regard to their preferences (the βs are identical for all respondents). This is a strong and often invalid assumption. Therefore, we use a mixed multinomial logit model[32] (Carlsson et al. 2003; Hensher and Greene 2003) that incorporates heterogeneity of preferences. Assuming a linear utility, the utility gained by person *q* from alternative *i* in choice situation *t* is given by

$$U_{qit} = \alpha_{qi} + \beta_q X_{qit} + \gamma_i Y_q + \varepsilon_{qit} \tag{8}$$

where X_{qit} is a vector of non-stochastic explanatory variables, and Y_q is a vector of socio-economic characteristics. The parameters α_{qi} and γ_i represent an intrinsic preference for the alternative and the heterogeneity of preferences respectively. Following standard practice for logit models we assume that ε_{qit} is independent and identically distributed extreme value type I.

We assume the density of β_q is given by $f(\beta \mid \Omega)$ where the true parameter of the distribution is given by Ω. The conditional choice probability alternative *i* for individual *q* in choice situation *t* is logit[33] and given by

$$L_q(\beta_q) = \prod_t \frac{\exp(\alpha_{qi} + \beta_q X_{qit} + \gamma_i Y_q)}{\sum_{j \in J} \exp(\alpha_{qj} + \beta_q X_{qjt} + \gamma_j Y_q)}. \tag{9}$$

---

[31] The β's represent marginal utilities ($\beta_k = \partial U / \partial Z_k$)
[32] Also referred to as mixed logit, hybrid logit and random parameter logit, random coefficient logit model
[33] The remaining error term is iid extreme value.

The unconditional choice probability for individual q is given by,

$$P_q(\Omega) = \int L_q(\beta) f(\beta \mid \Omega) d\beta \,. \tag{10}$$

The above form allows for the utility coefficients to vary among individuals while remaining constant among the choice situations for each individual (Carlsson et al. 2003; Hensher et al. 2005). There is no closed form for the above integral, therefore P_q needs to be simulated. The unconditional choice probability can be simulated by drawing R drawings of β, β_r, from $f(\beta \mid \Omega)$ [34] and then averaging the results to get

$$\tilde{P}_q(\Omega) = \frac{1}{R} \sum_{r \in R} L_q(\beta_r) \,. \tag{11}$$

The interpretation of the coefficient values for the above mixed multinomial model is complicated. Therefore following Carlsson et al. (2003) we calculate the marginal rates of substitution between the attributes using the coefficient for cost as numeraire and we interpret the ratios as average marginal WTP for a change in each attribute.

3.4.5 Econometric Specification

We use three econometric specifications to test for robustness of the results and to incorporate individual heterogeneity.

The conditional logit is:

$$V_{ni} = \beta_1 X_{richness} + \beta_2 X_{density} + \beta_3 X_{endangered} + \beta_4 X_{wildflowers} + \beta_5 X_{burning} + \beta_6 X_{distance} + \beta_7 X_{cost} + \varepsilon_{ni} \tag{12}$$

The mixed multinomial logit is:

$$V_{ni} = \beta_{1n} X_{richness} + \beta_{2n} X_{density} + \beta_{3n} X_{endangered} + \beta_{4n} X_{wildflowers} + \beta_{5n} X_{burning} + \beta_{6n} X_{distance} + \beta_{7n} X_{cost} + \varepsilon_{ni}$$

[34] Typically $f(\beta \mid \Omega)$ is assumed to be either normal or log-normal but it needs to be noted that the results are sensitive to the choice of the distribution.

(13)

The mixed multinomial logit with interaction terms is:

$$\begin{aligned} V_{ni} = {} & \beta_{1n} X_{richness} + \beta_{2n} X_{density} + \beta_{3n} X_{endangered} + \beta_{4n} X_{wildflowers} \\ & + \beta_{5n} X_{burning} + \beta_{6n} X_{distance} + \beta_{7n} X_{cost} + \beta_{8n} X_{richness} * X_{density} \\ & + \beta_{9n} X_{density} * X_{endangered} + \beta_{10n} X_{endangered} * X_{richness} \\ & + \beta_{11n} X_{cost} * Y_{grassland\ near?} + \beta_{12n} X_{cost} * Y_{nature\ reserve\ near?} \\ & + \varepsilon_{ni} \end{aligned} \tag{14}$$

This most complex specification (14) includes three variables that are interactions between the conservation success attributes. A significant and positive coefficient on an interaction term implies that the respondent has higher marginal utility for increases in one conservation success measure when the levels of the other conservation success terms are high. This would lead to concave TWTP contours between conservation attributes as depicted in Figure 3.3a. A significant and negative coefficient on the interaction terms implies the opposite and would lead to convex TWTP contours as depicted in Figure 3.3c. If the coefficient is insignificant, then the contours are linear (Figure 3.3b); this is the standard implicit assumption of most CE econometric specifications.

This specification also includes terms that interact the cost attribute with person-specific dummy variables that indicate the presence of grasslands and the presence of non-grassland natural areas nearby. These interaction terms allow us to analyze the impact of existing natural areas on the WTP for a new hypothetical grassland. If the coefficient is positive (negative) and significant this implies that respondents who have a nearby natural area are willing to pay more (less) to restore a new grassland.

The conditional logit model was estimated using the built in function within STATA. The mixed multinomial logit and the mixed multinomial logit with interaction terms were estimated using the user written STATA routine by Hole (Hole 2007).

3.5. Results and Discussion

Out of the 2000 surveys that were mailed out, 48 were undeliverable. Of those that were delivered, 316 surveys were returned out of which 263 were complete yielding 1578 choice question observations with an overall response rate of 16.19%. Each of the 18 different survey versions was returned at least 10 times. This ensures that each of the 54 choice profiles was represented in the final analysis. Of the 316 surveys that were returned, 196 were surveys that included the dollar bill. Therefore, including the dollar bill increased the response rate by 63%. Table 3.2 compares the demographic characteristics of the state and the respondents, showing our sample to be reasonably representative of adults in the state.

3.5.1 Testing for Preference Stability.

There is an ongoing discussion in the non-market valuation literature regarding preference stability in choice experiment surveys with repeated choices. Though many studies (Carlsson and Martinsson 2001; Johnson and Bingham 2001; Hanley et al. 2002; Homes and Boyle 2005; Clark and Friesen 2008; Ladenburg and Olsen 2008; Savage and Waldman 2008; Bateman et al. 2008; Bush et al. 2009; Brouwer et al. 2010; Carlsson et al. 2010; Day and Prades 2010) have analyzed ordering and learning effects in choice experiment surveys, there is no clear consensus on the presence of ordering and learning effects. We contribute to this ongoing discussion by using a novel experiment design to test for ordering and learning effects in choice experiment surveys.

The experimental design for the choice experiment survey required 9 unique surveys each with 6 choice questions. We created the experimental framework for testing learning and ordering effects by first creating a second set of surveys by reversing the order of the 6 choice questions and second by repeating the first choice question at the end. This gives us 18 unique surveys with 7 choice questions in each survey.

The results for testing for learning are shown in Table 3.3.a. The results corresponding to dropping the first choice are on the left and the results corresponding to dropping the last choice are on the right. The significance of two of the interactions terms changes between the two sets of results, which implies that there are significant learning effects. In contradiction to Carlsson et al. 2010, we find that dropping the first choice question does not significantly influence the error variance of the estimates..

The results for testing for ordering effects are shown in Table 3.3.b. The first sets of results correspond to the initial 9 versions of the survey. The second sets of results correspond to the second 9 versions of the survey where the order of the choice questions were reversed. The columns again refer to dropping the first choice and the last choice respectively. There are noticeable ordering effects. For the first 9 versions of the survey, two of the interaction terms are not significant whereas when the order of the choice questions is reversed these variables become significant. We believe that this indicates there are ordering effects but they are limited to the interactions terms. We drop the first choice question to account for learning effects and use the pooled data from all 18 versions for the remainder of the analysis to overcome ordering effects.

3.5.2 Main Results.

The results for the main-effects regressions (conditional logit and mixed logit) models are presented in Table 3.4. These specifications do not include interaction terms. The last column of

Table 3.4 indicates that individual heterogeneity is significant for many attributes and should be taken into consideration. However, the parameter estimates are qualitatively similar across the two models. The three conservation attributes and wildflowers all have positive and significant coefficients, while distance and cost are negative and significant.

For each set of results we calculate the marginal willingness to pay (MWTP) for each attribute by dividing the coefficient for each attribute by the coefficient for cost as

$$MWTP_i = \frac{\beta_i}{\beta_{cost}} \qquad (15)$$

The resulting MWTP values are shown in Table 3.5. Though the coefficient values for the conditional logit and the mixed logit models vary in magnitude, the MWTP values for each attribute is similar for both models. The coefficient estimates should not be compared to each other directly since the units for each attribute differ. All three of the conservation success measures (species richness, population density and endangered species) have significant per household values. A typical person is willing to pay $1.13 each year to have an additional bird species present in the grassland, and the value of an endangered species is a much higher $9.09, while increasing the population density of birds in a grassland by 1 additional bird per acre is worth $1.60. This latter result reinforces the findings by Loomis and Larson (1994) and Fletcher and Koford (2002) that wildlife population density is an important variable affecting the public's WTP for restoring habitats.

The results for the mixed logit model with interaction terms are presented in Table 3.6. The coefficient for the interaction of the *cost* and the *grassland near* variable is negative. This implies that respondents who live near existing grassland areas have a higher MWTP for each of the attributes. This result contradicts what would be predicted by standard neoclassical consumer economics. This finding could be evidence of endogenous preferences - individuals who consume and experience a good can have a higher WTP for the good than individuals who have not experienced a good. It could alternatively be argued that this result is caused by locational sorting wherein respondents who have an inherent preference for grasslands choose to live close to them. We note that people with high values for grasslands may also have relatively high values for other natural areas, but the interaction effect for non-grassland natural areas being nearby is not significant in the regression; this might imply that the positive coefficient on the interaction of cost with the grassland near dummy is more likely caused by endogenous preferences than by sorting.

The two-way interaction terms between species richness, population density and endangered species are all significant and negative; the marginal value of one conservation feature is lower when the levels of the other feature is high. Figure 3.4 shows the TWTP as a function of species richness for different levels of population density. The TWTP increases as the value of species richness increases. The three lines in Figure 3.4 correspond to different levels of population density. As population density increases the TWTP at each level of species richness increases. When the interaction terms are set to zero (Figure 3.4.a) the increase in TWTP caused by higher population density is the same at every species richness level (the lines are parallel). When the interaction terms are included (Figure 3.4.b), the slope of the TWTP-species richness line decreases as the level of population density increases. This illustrates the relationship between preferences over any two conservation goals; here an increase in species richness has a smaller impact on TWTP at high levels of population density than at low levels of population density.

Further, the significant interaction terms implies that the total WTP (TWTP) curves are non-linear as depicted in Figure 3.5, which depicts the TWTP contour in species richness and population density space (similar to a utility function in two good space). Figure 3.5.a contains a TWTP contour for a TWTP of $80. This contour shows the combination of species richness and population density that yield a TWTP of $80. When the interaction terms are ignored the TWTP contour is linear, indicating a fixed marginal rate of substitution. When the interaction terms are included the TWTP contour is concave, indicative an increasing marginal rate of substitution. Figure 3.5.b shows the substitution between species richness and population density for different levels of TWTP and number of endangered species. The TWTP contour for $70 lies below the TWTP for $80. As the value of endangered species increases, the TWTP contour shifts inwards since a smaller amounts of species richness and population density are required to reach the $70 TWTP contour.

Next we characterize the bundle of conservation success attributes that will provide the largest TWTP while holding other attributes of a grassland constant. We solve a simple constrained maximization problem where the TWTP is maximized as a function of the conservation success variables. The results are presented in Table 3.8. The first column indicates whether physical constraints are present; the first sets of results are unconstrained while the second sets of results assume physical limits on the levels of some attributes. The second column indicates the budget constraint and the third column indicates the stylized costs. We assume that each of the conservation success attributes can be produced independently and that the costs are given per unit of each attribute. We solve the problem for a range of total cost values to show how the result changes with the cost. Column four indicates whether the results include the interaction terms. Columns five through seven report the resulting optimal values of the conservation success variables and column eight contains the corresponding TWTP amount.

The first sets of results correspond to a scenario without physical constraints. When the costs are all \$1 (the cost ratio is1:1:1), for both the scenarios with and without interaction terms, the result is a corner solution where only the endangered species variable has a positive value. This is to be expected given the concave TWTP curves and the fact that endangered species has the highest marginal value. Given that it is relatively difficult to manage a grassland to attract endangered species, we increase the relative cost of endangered species. When the cost of endangered species in increased to \$10 (cost ratio of 1:1:10), the solution changes so that only the population density variable has a positive value. Again this result makes sense since population density has the second largest marginal value. These corner solutions are to be expected given the nature of the indifference curves depicted in Figure 3.4. Given the slope of the cost function the unbounded utility maximizing bundle will consist of just one attribute.

Next we characterize the TWTP-maximizing bundle when physical constraints are imposed on the levels of conservation goals that can be achieved. The results show that the TWTP-maximizing bundle is one with high values for the attributes that have a higher marginal contribution to the overall TWTP. For example, when the budget is unconstrained the scenario without interaction terms selects the maximum possible values for each of the three conservation success attributes. When the interaction terms are included, only the population density variable and the endangered species variable have positive values. This result makes sense since the interaction terms are negative and if the species richness variable had a positive value the net effect of its presence would be a decrease in TWTP due to the interaction terms. When the budget is constrained, for the scenario without interaction terms, the TWTP maximizing solution is the solution to the knapsack problem.[35] For the scenario with interaction terms, the conservation success variable with the lowest contribution, species richness, has zero value.[36]

Finally, we calculate the total WTP (TWTP) for a hypothetical grassland with realistic attribute values. Due to the various interaction terms, the result is best represented as the table shown in Table 3.7. We estimate the TWTP for a 100 acre hypothetical grassland with 30 different bird species, 15 individual birds per acres, 6 endangered species, 60% wildflower coverage, and controlled burning once every year and when no non-grassland nature area is nearby. The TWTP ranges between $60 and $109 per household per year. The results indicate that being near an existing grassland increases the TWTP for an additional grassland by as much as 43% (when the new grassland is 10 miles away). Further, as the distance to the restored grassland increases from 10 miles to 100 miles the TWPT decreases by as much as 28%.

3.6. Conclusion

We analyze the structure of public willingness to pay for different attributes of grassland ecosystems using a choice experiment survey. This work yields several findings that have broad implications for conservation planning and environmental valuation. First, we find that several features of an ecosystem that are used as measures of conservation success - species richness, population density, and presence of endangered species - have large positive marginal values.

[35] Obtain as much as allowed from the attribute that has a highest marginal contribution to the objective function, then as much as allowed from the attribute with the second highest marginal contribution and so on.
[36] If the species richness value also had a positive amount the net effect will be a decrease in TWTP due to the interaction terms

Much of the work on optimal protected-area planning and design uses a single measure of conservation success as the objective to be maximized. Our results imply that when there are physical tradeoffs between conservation outcomes (e.g. one can increase the population of a single species such as pheasant, but in doing so one might lower species richness) planners should be careful to consider all conservation success measures in order to maximize the social welfare obtained from conservation and restoration efforts.

Second, in an effort to analyze the structure of the preferences for the conservation success attributes in more detail we use a specification that contains pairwise interactions of the conservation success terms. We find that the values people place on any one conservation outcome is lower when the levels of other conservation outcomes are high; in other words, people seem to view these feature as substitutes rather than complements. This means, for example, that the value to society of a project that maximizes species richness will vary across sites that have different levels of wildlife population density and numbers of endangered species.

Given that restoration ecologists are able to determine the levels of species richness, population density and the presence of endangered species when undertaking conservation efforts, our results emphasize the importance of considering the levels of all these attributes when conducting restoration efforts, optimal protected area planning models, and cost benefit analysis for conservation and restoration of ecosystems.

We also show that as a result of the concave TWTP contours, the TWTP maximizing grassland only has positive values for one of the conservation success terms (there is a corner solution). If the signs on the interaction terms were reversed, i.e. the willingness to pay for a given attribute increased with the values of the other attributes, the indifference curves would be convex and this would have resulted in interior solutions with positive values for multiple conservation success attributes. These results also emphasize the importance of including interaction terms when studying the WTP for attributes that can be treated as either complements or substitutes by the respondent.

Third, we find that respondents who live near existing grassland areas have a higher MWTP for restoring additional grasslands. This result contradicts what would be predicted by standard neoclassical economics- the marginal value of a good will decline with its total quantity. Our result may reflect the existence of endogenous preferences - individuals who consume and experience a good learn to appreciate and enjoy it and can therefore can have a higher WTP than individuals who have not experienced the good. We recognize that this finding could be caused by locational sorting. However, as discussed earlier, the fact that the WTP for an additional grassland is not correlated with the presence of nearby non-grassland natural areas leads us to believe our result is evidence of endogenous preferences. We will control for possible endogeneity of proximity to grassland in future versions of this work. If the result is robust, it has implications for conservation planning in terms of locating new conservation areas; for example the welfare maximizing conservation strategy may be to have similar ecosystem types partially clustered in the landscape.

Finally, this study is the first to generate value estimates for the WTP to conserve and restore grasslands, an ecosystem type that is disappearing throughout North America. This study provides valuable information to conservation planners and ecologists engaged in restoring and conserving ecosystems regarding the values placed on grasslands by the public.

The results allow policy makers to calculate the total willingness to pay for a grassland with varied characteristics. For the plausible grassland described in the results section, the annual value per household ranges between $60 and $109.[37] This information is especially important in places like Illinois where some lands could be potentially be restored as wetland, tallgrass prairie or forest with different restoration and management techniques.[38]

The results we present allow conservation organizers and land use planners to effectively conduct a cost benefit analysis of restoring grasslands, and improve restoration planning decisions about the attributes of restored grasslands. The findings also raise provocative questions about the standard economic assumption that marginal value of environmental goods diminishes with total quantity; those questions should be further explored in future research.

3.7. Future Work

Given the manner that the interaction terms are currently specified in the econometric specification, at high levels of one species conservation success variable, the other species conservation success variables become economics bad (as opposed to economic goods). This is caused by the linear specification and the negative coefficients on the econometric specification. We are currently exploring alternate specification that could prevent the conservation success attributes from becoming economic bads.

[37] For a 100 acre hypothetical grassland with 30 different bird species, 15 individual birds per acres, 6 endangered species, 60% wildflower coverage, and controlled burning once every year.

[38] To put those values in context, we list here value estimates that have been obtained for other ecosystems. Boyer and Polasky (2004) give examples of stated preference surveys that yield WTP for wetlands in the range of $15 (1987$) - $87 (1998$) per hectare per year. Brander et al (2006) conduct a comprehensive summary of stated preference studies on wetlands and find the median willingness to pay is approximately 200 1995 $ per hectare. per year. Heimlich et al. (1998) find empirical estimates of the WTP for wetlands that range between $0.02 to $8,924 per hectare. Barrio and Loureiro (2010) conduct a meta-analysis of CV studies of forests and find values that range between $0.75 (ppp 2008$) - $490 (ppp 2008$).

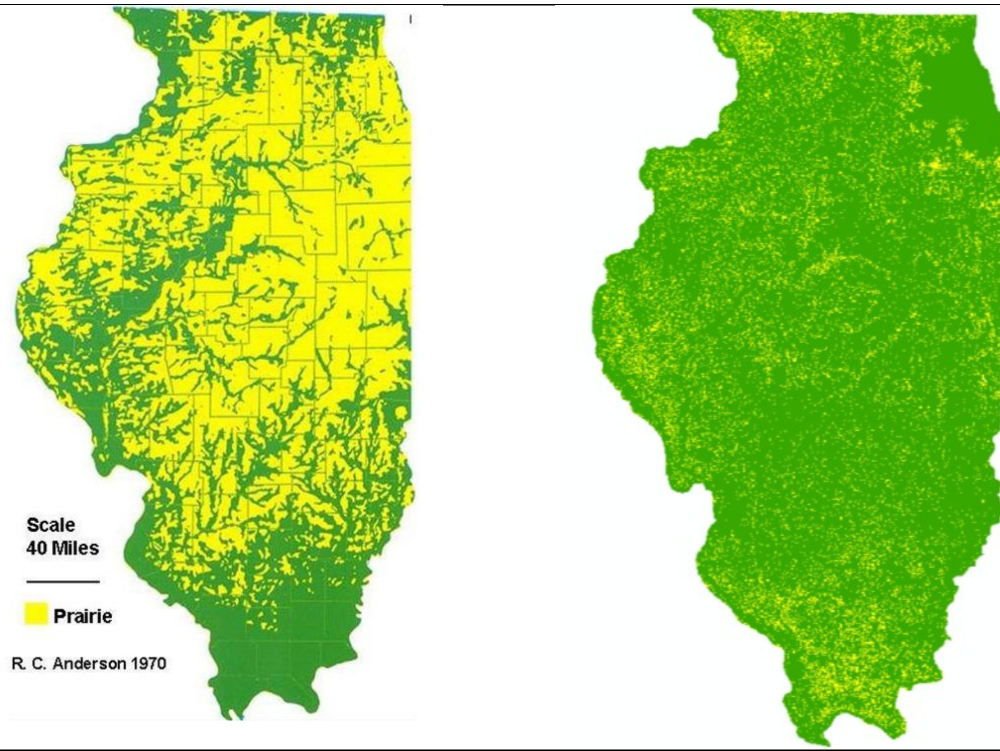
As mentioned there may be a potential endogeneity issue with the grassland near variable. We are currently working on accounting for this endogeneity. We are exploring the use of actual grassland near variables (as opposed to the self-reported variables) to account for any self-reporting bias, but this variable would still suffer from endogeneity arising from the respondents location choice being correlated with their proximity to grasslands.

3.8. Tables and Figures

Figure 3.1: Grasslands in North America

Source: (Nature Conservancy, 2008)

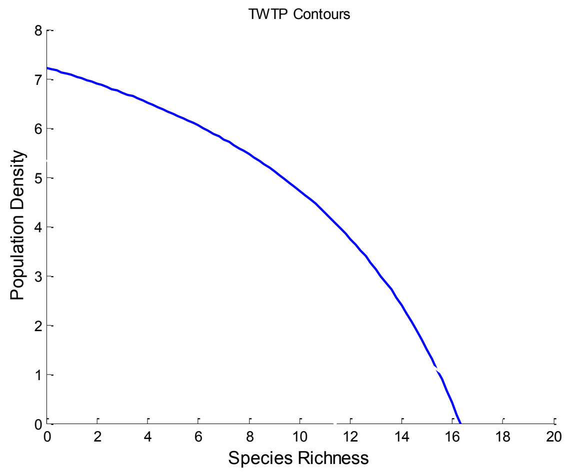
Figure 3.2: Grasslands in Illinois



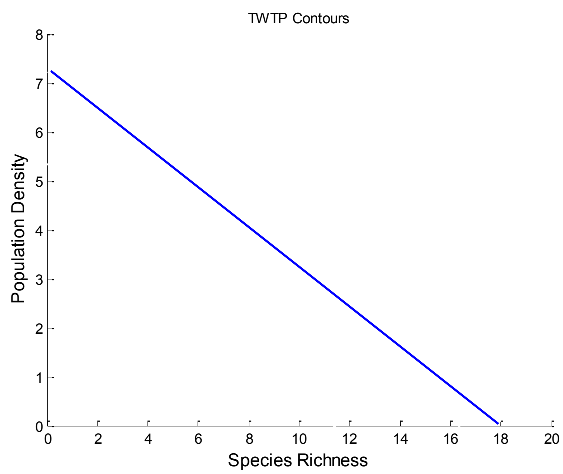
Panel 2.a: Map of Historic Prairies in Illinois from 1820 (Anderson 1970)

Panel 2.b Map of Rural Grassland in Illinois from 2000(Created from INGDCH Land Cover data)

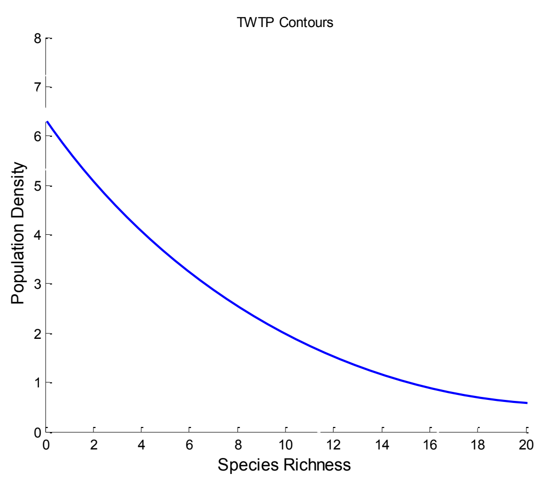
Figure 3.3: Concave vs. Convex TWTP Contours



Panel 4.a Concave Interaction Terms

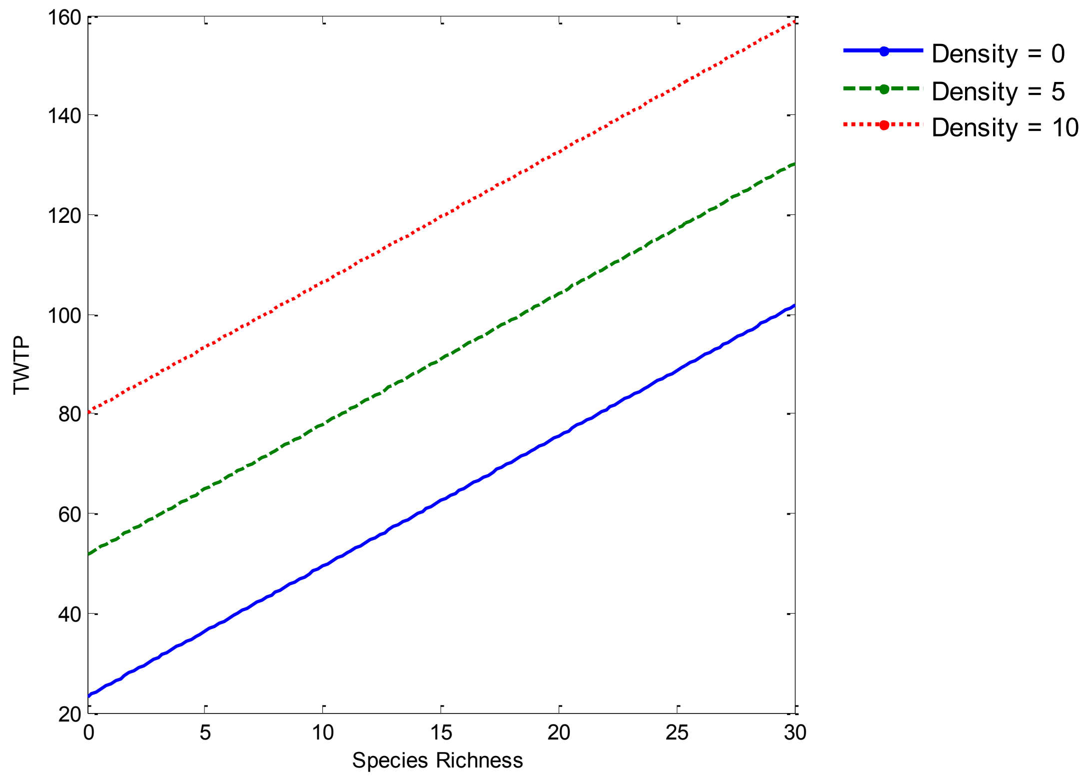


Panel 4.a Linear Interaction Terms

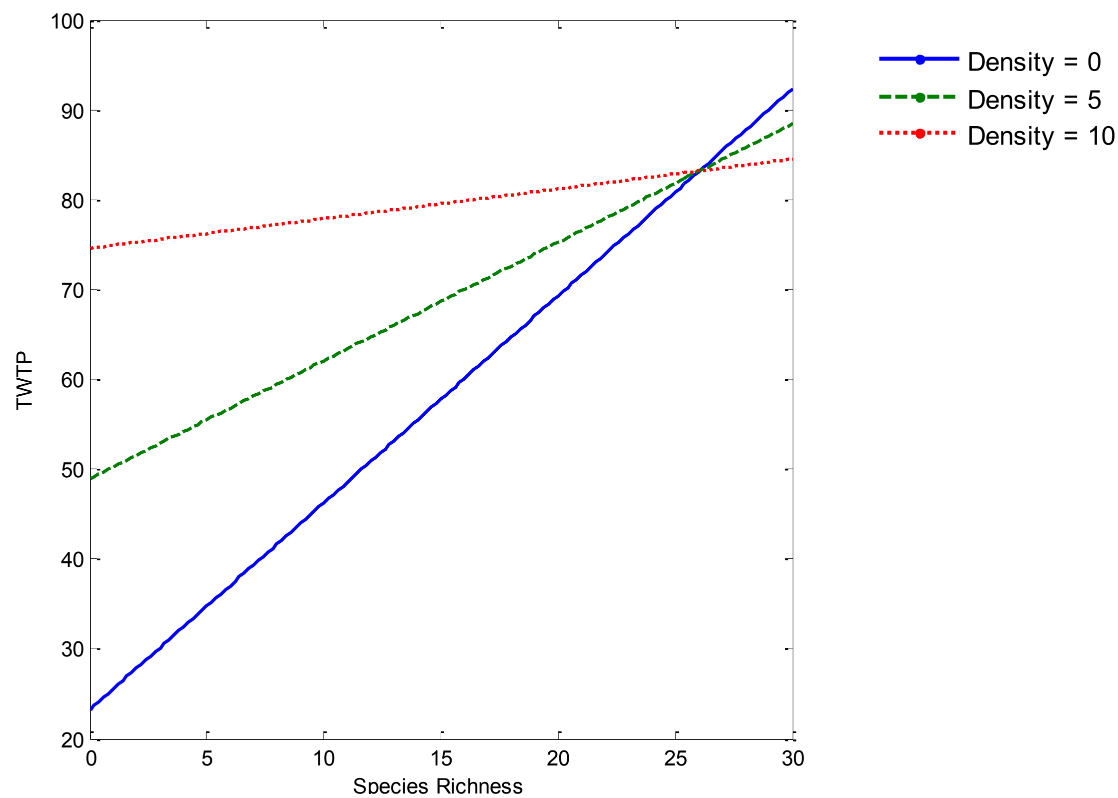


Panel 4.a Convex Interaction Terms

Figure 3.4: Species Richness vs TWTP as Density Changes



a. With interaction terms set to zero



b. With positive interaction terms

Figure 3.5.a: TWTP with and without interaction terms

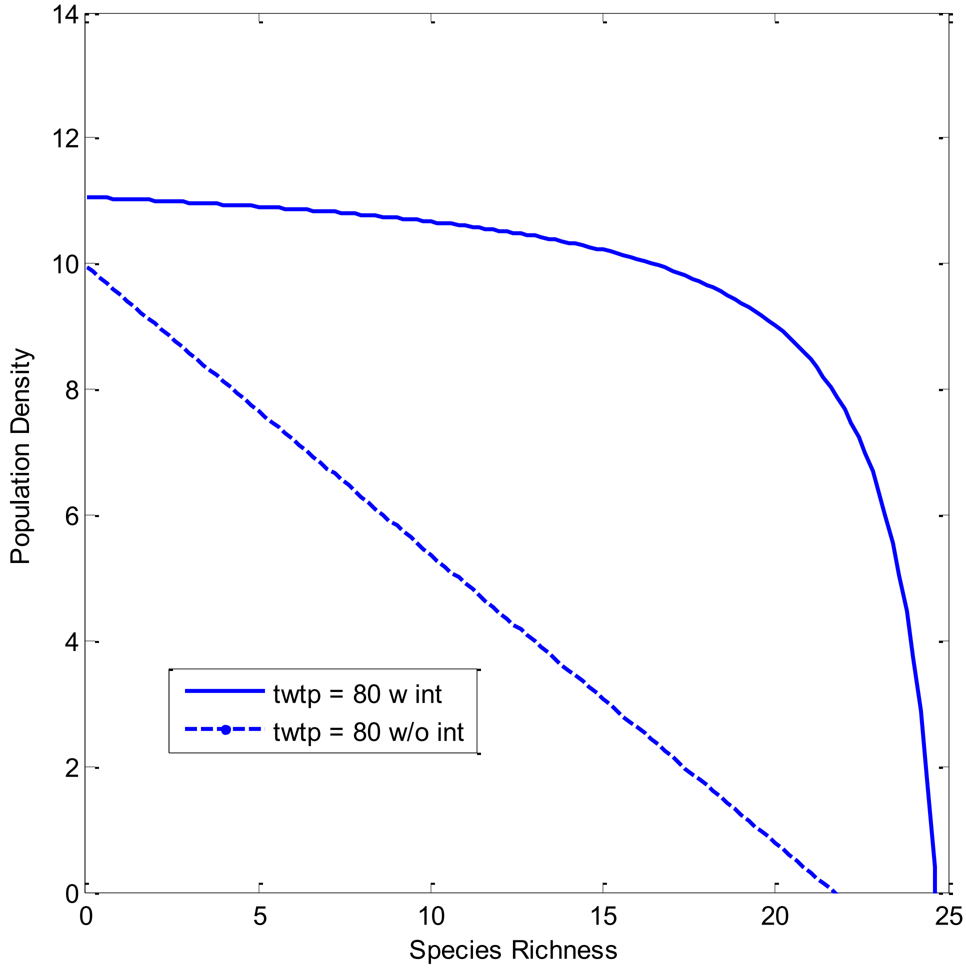


Figure 3.5.b: TWTP Curves over changing attribute values

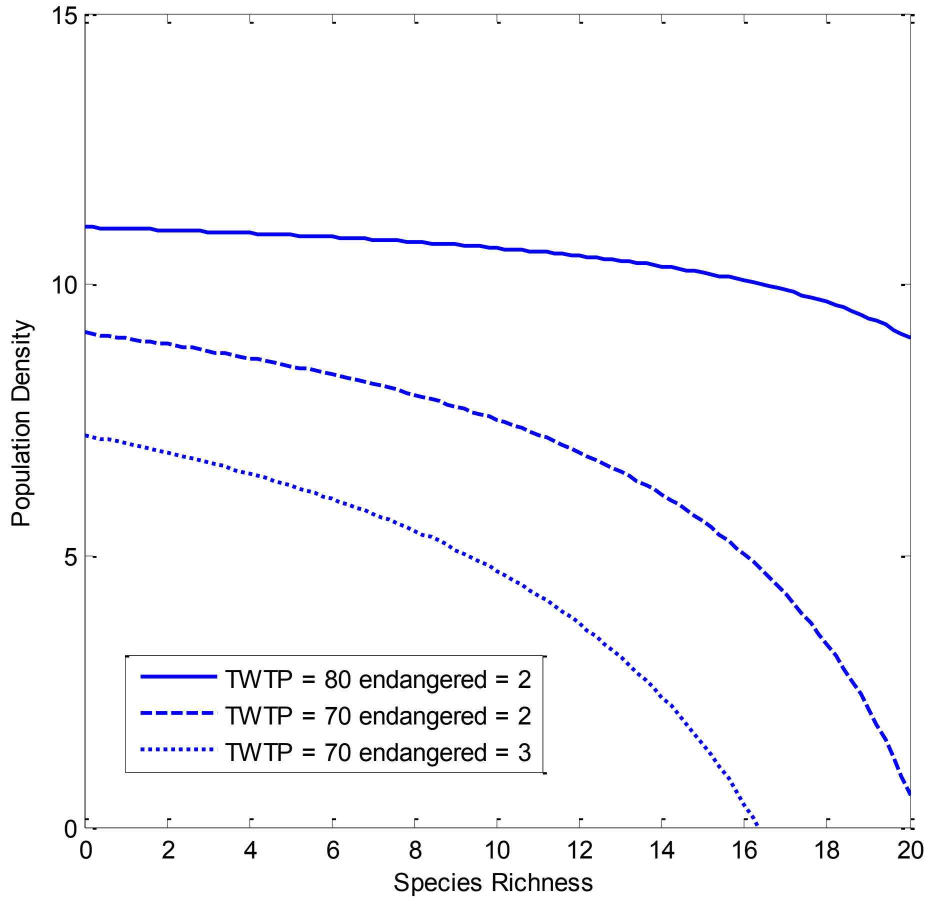


Table 3.1: Attributes and levels for survey instrument

Attribute	Description	Levels
Number of Bird Species	The number of different bird species in the restored area. A high number means you are more likely to see many different **kinds of birds** in the restored area.	30 different species 20 different species 10 different species
Density of Birds	The number of individual birds (from all species) within an acre. A high number means you are more likely to see a large **number of individual birds** in the restored areas. They may be all the same type, or they may be several different types.	15 individuals per acre 10 individuals per acre 5 individuals per acre
Number of endangered species	The number of different endangered or threatened bird species that will live in the restored area.	6 endangered or threatened species 3 endangered or threatened species 0 endangered or threatened species
Amount of wildflowers	The percentage of restored land area that will be covered by wildflowers. A higher percentage means you are more likely to see more wildflowers in the restored area.	60% covered in wildflowers 40% covered in wildflowers 20% covered in wildflowers
Use of prescribed burning	The possible use of prescribed burns to manage the grassland.	No prescribed burning Prescribed burning once every other year. Prescribed burning once every year
Distance to restored area	The distance to the restored area from your home. This feature ranges from 10 miles (between 8 to 12 minutes) to 100 miles (between 1 1/2 to 2 hours)	10 miles 50 miles 100 miles
Annual cost to your household	The fee that your household will have to pay every year to restore and maintain the grassland.	This value will range from $0 to $100

Table 3.2: Comparison of state population and sample

Variable	State[a]	Dataset
Average age over 18(years)[c]	47	55 (15)
Income, \$1,000 (median household, 2009)	54	50 – 75
Education		
High school completed	86%	96% (20)
Bachelors degree completed	30%	47% (50)
Female	51	41 (49)
Children under 18	2.5	2.7 (4.4)

[a]Based on http://quickfacts.census.gov/qfd/states/17000.html
[b]2010 census, calculated from http://factfinder2.census.gov/

Table 3.3.a: Testing for Learning

Variable	Drop First Choice		Drop Last Choice	
	Coefficient	SE	Coefficient	SE
Main Effects				
Species richness	0.140***	0.024	0.133***	0.023
Population density	0.308***	0.044	0.346***	0.048
Endangered Species	0.568***	0.115	0.696***	0.135
Wildflowers	0.017***	0.005	0.020***	0.005
Prescribed burning	-0.067	0.093	-0.172	0.106
Distance	-0.013***	0.002	-0.016***	0.003
Cost	-0.062***	0.008	-0.052***	0.006
Richness X Density	-0.011***	0.002	-0.011***	0.002
Density X Endangered	-0.014	0.009	-0.026***	0.009
Endangered X richness	-0.008*	0.004	-0.007	0.004
Number of Observations	4734		4722	
LR chi2(7)	791.64		790.7	
Prob > chi2	0.00		0.00	

***significant at 1%, **significant at 5%, *significant at 10%

Table 3.3.b: Testing for Ordering

Original Ordering

Variable	Drop First Choice		Drop Last Choice	
	Coefficient	SE	Coefficient	SE
Main Effects				
Species richness	0.173***	0.042	0.175***	0.039
Population density	0.328***	0.068	0.331***	0.077
Endangered Species	0.494***	0.191	0.393**	0.177
Wildflowers	0.018**	0.008	0.018***	0.007
Prescribed burning	0.012	0.142	0.015	0.146
Distance	-0.017***	0.006	-0.015***	0.004
Cost	-0.046***	0.009	-0.052***	0.010
Richness X Density	-0.013***	0.004	-0.014***	0.004
Density X Endangered	-0.006	0.014	0.006	0.014
Endangered X richness	-0.011	0.008	-0.007	0.007
Number of Observations	2358		2352	
LR chi2(7)	428.9		453.12	
Prob > chi2	0.00		0.00	

***significant at 1%, **significant at 5%, *significant at 10%

Reverse Ordering

Variable	Drop First Choice		Drop Last Choice	
	Coefficient	SE	Coefficient	SE
Main Effects				
Species richness	0.141***	0.033	0.164***	0.035
Population density	0.368***	0.068	0.355***	0.063
Endangered Species	0.880***	0.197	0.858***	0.178
Wildflowers	0.018***	0.007	0.015*	0.008
Prescribed burning	-0.214	0.149	-0.071	0.138
Distance	-0.016***	0.004	-0.016***	0.004
Cost	-0.069***	0.009	-0.059***	0.008
Richness X Density	-0.011***	0.003	-0.012***	0.003
Density X Endangered	-0.034***	0.013	-0.033***	0.012
Endangered X richness	-0.010	0.007	-0.011*	0.007
Number of Observations	2376		2370	
LR chi2(7)	367.7		367.23	
Prob > chi2	0.00		0.00	

***significant at 1%, **significant at 5%, *significant at 10%

Table 3.4: Regression Results for the Conditional Logit and Mixed Logit Models

Variable	Conditional Logit		Mixed Logit		
	Coefficient	SE	Coefficient	SE	SD^
Species richness	0.017***	0.004	0.029***	0.010	Significant
Population density	0.024***	0.008	0.092***	0.018	
Endangered Species	0.135***	0.014	0.321***	0.043	Significant
Wildflowers	0.013***	0.002	0.032***	0.005	Significant
Prescribed burning	-0.016	0.042	0.121	0.099	Significant
Distance	-0.005***	0.001	-0.011***	0.003	Significant
Cost	-0.015***	0.001	-0.042***	0.005	Significant
Number of Observations	4734		4734		
Log Likelihood	-1534.26		-1169.70		
LR chi2(7)	398.70		729.13		
Prob > chi2	0.00		0.00		

***significant at 1%, **significant at 5%, *significant at 10%

^Significance of standard deviations at 10% or less when incorporating individual heterogeneity

Table 3.5: Marginal Willingness to Pay Estimates

Attribute	Clogit	Mixlogit
Species Richness	$1.13	$0.71
Bird Density	$1.60	$2.22
Endangered Birds	$9.09	$7.73
Wildflowers	$0.86	$0.77
Burning	-$1.08	$2.92
Distance	-$0.31	-$0.25

Table 3.6: Results for the Mixed Logit Model with Interaction Terms

Variable	Mixed Logit with Interaction Terms		
	Coefficient	Standard Errors	SD^
Main Effects			
Species richness	0.155***	0.028	Significant
Population density	0.337***	0.052	Significant
Endangered Species	0.692***	0.140	Significant
Wildflowers	0.020***	0.006	Significant
Prescribed burning	-0.025	0.110	Significant
Distance	-0.015***	0.003	Significant
Cost	-0.084***	0.015	Significant
Conservation Success Interaction Terms			
Richness X Density	-0.012***	0.003	Significant
Density X Endangered	-0.017*	0.010	
Endangered X richness	-0.009*	0.005	Significant
Complementarity Interaction Terms			
Grassland Near X Cost	0.025**	0.011	
Nature Near X Cost	0.009	0.014	Significant
Number of Observations	4734		
Log Likelihood	-1112.74		
LR chi2(7)	811.34		
Prob > chi2	0.00		

***significant at 1%, **significant at 5%, *significant at 10%

^Significance of standard deviations at 10% or less when incorporating individual heterogeneity

Table 3.7: TWTP for a Hypothetical Grassland

Distance	Grassland Near	
	0	1
10	$66	$93
	(47-85)	(47-140)
100	$49	$70
	(33 - 65)	(33 - 107)

Note: The 95% confidence interval for each estimate is given within the parentheses.

Table 3.8: Constrained Maximum TWTP

Physical Constraints	Budget Constraint	Cost Ratio	Interaction Terms	Richness	Density	Endangered	TWTP
None	$100 total	Equal (1:1:1)	No	0	0	100	$1172.3
			Yes	0	0	100	$1172.3
	$100 total	1:1:10	No	0	100		$569.9
			Yes	0	100	0	$569.9
Application bounds[39]	Unconstrained	Equal (1:1:1)	No	30	15	6	$234.2
			Yes	0	15	6	$130.12
	$30 total	Equal (1:1:1)	No	9	15	6	$179.22
			Yes	0	15	6	$130.12
	$15 total	Equal (1:1:1)	No	0	9	6	$106.12
			Yes	0	9	6	$121.45

[39] 0 ≤ Species richness ≤ 30, 0 ≤ Population density ≤ 15, 0 ≤ Endangered Species ≤ 6,

3.9. References

Adamowicz, W., P. Boxall, M. Williams and J. Louviere, 1998, Stated preference approaches for measuring passive use values: choice experiments and contingent valuation, American Journal of Agricultural Economics 80, 64-75.

Adamowicz, W., J. Swait, P. Boxall, J. Louviere and M. Williams, 1997, Perceptions versus objective measures of environmental quality in combined revealed and stated preference models of environmental valuation, Journal of Environmental Economics and Management 32, 65-84.

Adger, W.N., K. Brown, R. Cervigni and D. Moran, 1995, Total economic value of forests in Mexico, Ambio , 286-296.

Ajzen, I., 1991, The theory of planned behavior, Organizational behavior and human decision processes 50, 179-211.

Ando, A., J. Camm, S. Polasky and A. Solow, 1998, Species distributions, land values, and efficient conservation, Science 279, 2126.

Ando, A.W. and P. Shah, 2010, Demand-side factors in optimal land conservation choice, Resource and Energy Economics 32, 203-221.

Askins, R.A., R. Askins and J. Zickefoose, 2002, Restoring North America's Birds: Lessons from Landscape Ecology. (Yale Univ Pr).

Baarsma, B.E., 2003, The valuation of the IJmeer nature reserve using conjoint analysis, Environmental and Resource Economics 25, 343-356.

Bateman, I.J., B.H. Day, S. Georgiou and I. Lake, 2006, The aggregation of environmental benefit values: Welfare measures, distance decay and total WTP, Ecological Economics 60, 450-460.

Birol, E., K. Karousakis and P. Koundouri, 2006, Using a choice experiment to account for preference heterogeneity in wetland attributes: the case of Cheimaditida wetland in Greece, Ecological Economics 60, 145-156.

Bowles, S., 1998, Endogenous preferences: The cultural consequences of markets and other economic institutions, Journal of economic literature 36, 75-111.

Boxall, P.C., W.L. Adamowicz, J. Swait, M. Williams and J. Louviere, 1996, A comparison of stated preference methods for environmental valuation, Ecological Economics 18, 243-253.

Boyer, T. and S. Polasky, 2004, Valuing urban wetlands: a review of non-market valuation studies, Wetlands 24, 744-755.

Brennan, L.A. and W.P. Kuvlesky Jr, 2005, Invited Paper: North American Grassland Birds: An Unfolding Conservation Crisis? Journal of Wildlife Management 69, 1-13.

Cabeza, M., M.B. Araújo, R.J. Wilson, C.D. Thomas, M.J.R. Cowley and A. Moilanen, 2004, Combining probabilities of occurrence with spatial reserve design, Journal of Applied Ecology 41, 252-262.

Cameron, T.A. and J. Englin, 1997, Respondent Experience and Contingent Valuation of Environmental Goods* 1, Journal of Environmental Economics and Management 33, 296-313.

Carlsson, F., P. Frykblom and C. Liljenstolpe, 2003, Valuing wetland attributes: an application of choice experiments, Ecological Economics 47, 95-103.

Carlsson, F., R. Mørkbak and B. Olsen, 2010, The first time is the hardest: A test of ordering effects in choice experiments, rapport nr.: Working Papers in Economics 470 .

Carson, R.T., N.E. Flores and N.F. Meade, 2001, Contingent valuation: controversies and evidence, Environmental and Resource Economics 19, 173-210.

Christie, M., N. Hanley, J. Warren, K. Murphy, R. Wright and T. Hyde, 2006, Valuing the diversity of biodiversity, Ecological Economics 58, 304-317.

Copeland, T.E., W. Sluis and H.F. Howe, 2002, Fire season and dominance in an Illinois tallgrass prairie restoration, Restoration Ecology 10, 315-323.

Csuti, B., S. Polasky, P.H. Williams, R.L. Pressey, J.D. Camm, M. Kershaw, A.R. Kiester, B. Downs, R. Hamilton and M. Huso, 1997, A comparison of reserve selection algorithms using data on terrestrial vertebrates in Oregon, Biological Conservation 80, 83-97.

Earnhart, D., 2006, Using contingent-pricing analysis to value open space and its duration at residential locations, Land Economics 82, 17.

Fletcher, R.J. and R.R. Koford, 2002, Habitat and landscape associations of breeding birds in native and restored grasslands, The Journal of wildlife management 66, 1011-1022.

Gourlay, D. and B. Slee, 1998, Public preferences for landscape features: a case study of two Scottish environmentally sensitive areas, Journal of Rural Studies 14, 249-263.

Gowdy, J.M., 2004, The revolution in welfare economics and its implications for environmental valuation and policy, Land Economics 80, 239.

Haight, R.G., C.S. Revelle and S.A. Snyder, 2000, An integer optimization approach to a probabilistic reserve site selection problem, Operations research 48, 697-708.

Hanley, N., S. Mourato and R.E. Wright, 2001, Choice Modelling Approaches: A Superior Alternative for Environmental Valuatioin? Journal of economic surveys 15, 435-462.

Hanley, N., R.E. Wright and G. Koop, 2002, Modelling recreation demand using choice experiments: climbing in Scotland, Environmental and resource Economics 22, 449-466.

Hatch, D.A., J.W. Bartolome, J.S. Fehmi and D.S. Hillyard, 1999, Effects of burning and grazing on a coastal California grassland, Restoration Ecology 7, 376-381.

Heaton, D., 2000, Conserving local habitat for declining grassland birds, Skokie, IL: Bird Conservation Network .

Heimlich, R.E., K.D. Wiebe, R. Claassen, D. Gadsby and R.M. House, 1998, Wetlands and agriculture: Private interests and public benefits, Agricultural Economics Reports .

Hensher, D.A. and W.H. Greene, 2003, The mixed logit model: the state of practice, Transportation 30, 133-176.

Hensher, D.A., J.M. Rose and W.H. Greene, 2005, Applied Choice Analysis: A Primer. (Cambridge Univ Pr).

Hole, A.R., 2007, MIXLOGIT: Stata module to fit mixed logit models by using maximum simulated likelihood, Statistical Software Components .

Horne, P. and L. Petajisto, 2003, Preferences for alternative moose management regimes among Finnish landowners: A choice experiment approach, Land Economics 79, 472.

Howe, H.F., 1995, Succession and fire season in experimental prairie plantings, Ecology 76, 1917-1925.

Howe, H. and J. Brown, 1999, Effects of birds and rodents on synthetic tallgrass communities, Ecology 80, 1776-1781.

Hoyos, D., 2010, The state of the art of environmental valuation with discrete choice experiments, Ecological Economics 69, 1595-1603.

Huber, J. and K. Zwerina, 1996, The importance of utility balance in efficient choice designs, Journal of Marketing Research , 307-317.

Illinois Department of Natural Resources, 2010, Illinois Wildlife Action Plan, 2010.

Kharouba, H.M. and J.T. Kerr, 2010, Just passing through: Global change and the conservation of biodiversity in protected areas, Biological Conservation 143, 1094-1101.

Knopf, F.L., 1994, Avian assemblages on altered grasslands, Studies in avian biology 15, 247-257.

Kuhfeld, W.F., 2010, Marketing research methods in SAS experimental design, choice, conjoint, and graphical techniques, .

Lancaster, K.J., 1966, A new approach to consumer theory, The Journal of Political Economy 74, 132-157.

Lehtonen, E., J. Kuuluvainen, E. Pouta, M. Rekola and C.Z. Li, 2003, Non-market benefits of forest conservation in southern Finland, Environmental Science & Policy 6, 195-204.

Liebe, U., P. Preisendörfer and J. Meyerhoff, 2011, To pay or not to pay: Competing theories to explain individuals' willingness to pay for public environmental goods, Environment and Behavior 43, 106.

Loomis, J. and E. Ekstrand, 1997, Economic benefits of critical habitat for the Mexican spotted owl: a scope test using a multiple-bounded contingent valuation survey, Journal of Agricultural and Resource Economics 22, 356-366.

Loomis, J., P. Kent, L. Strange, K. Fausch and A. Covich, 2000, Measuring the total economic value of restoring ecosystem services in an impaired river basin: results from a contingent valuation survey, Ecological Economics 33, 103-117.

Loomis, J.B. and D.M. Larson, 1994, Total economic values of increasing gray whale populations: results from a contingent valuation survey of visitors and households, Marine Resource Economics 9, 275-286.

Louviere, J.J., D.A. Hensher and J.D. Swait, 2000, Stated Choice Methods: Analysis and Applications. (Cambridge Univ Pr).

Macmillan, D. and E. Duff, 1998, Estimating the non-market costs and benefits of native woodland restoration using the contingent valuation method, Forestry 71, 247.

Margules, C.R. and R.L. Pressey, 2000, Systematic conservation planning, Nature 405, 243-253.

Martin, L.M., K.A. Moloney and B.J. Wilsey, 2005, An assessment of grassland restoration success using species diversity components, Journal of Applied Ecology 42, 327-336.

Martin, L.M. and B.J. Wilsey, 2006, Assessing grassland restoration success: relative roles of seed additions and native ungulate activities, Journal of Applied Ecology 43, 1098-1109.

Mcfadden, D., 1974, Conditional Logit Analysis of Qualitative Choice Behavior, Frontiers in Econometrics .

Meyerhoff, J. and A. Dehnhardt, 2007, The European Water Framework Directive and economic valuation of wetlands: the restoration of floodplains along the River Elbe, European Environment 17, 18-36.

Meyerhoff, J., U. Liebe and V. Hartje, 2009, Benefits of biodiversity enhancement of nature-oriented silviculture: Evidence from two choice experiments in Germany, Journal of Forest Economics 15, 37-58.

Milon, J.W. and D. Scrogin, 2006, Latent preferences and valuation of wetland ecosystem restoration, Ecological Economics 56, 162-175.

Noss, R.F., E.T. LaRoe and J.M. Scott, 1995, Endangered ecosystems of the United States: a preliminary assessment of loss and degradation .

O'Hanlon, L., 2009, Knee-High Rainforest; Interview with the Nature Conservancy's Bob McCready
, 2011, 1.

O'Hara, S.U. and S. Stagl, 2002, Endogenous preferences and sustainable development* 1, Journal of Socio-economics 31, 511-527.

Önal, H., 2004, First-best, second-best, and heuristic solutions in conservation reserve site selection, Biological Conservation 115, 55-62.

Önal, H. and R.A. Briers, 2005, Designing a conservation reserve network with minimal fragmentation: a linear integer programming approach, Environmental Modeling and Assessment 10, 193-202.

Possingham, H., K. Wilson, S. Andelman and C. Vynne, 2010, Protected areas: goals, limitations, and design, .

Pressey, R.L., M. Cabeza, M.E. Watts, R.M. Cowling and K.A. Wilson, 2007, Conservation planning in a changing world, Trends in Ecology & Evolution 22, 583-592.

Primack, R.B., 1993, Essentials of Conservation Biology. (Sinauer Associates Sunderland).

Roe, B., K.J. Boyle and M.F. Teisl, 1996, Using Conjoint Analysis to Derive Estimates of Compensating Variation* 1, Journal of Environmental Economics and Management 31, 145-159.

Rolfe, J., J. Bennett and J. Louviere, 2000, Choice modelling and its potential application to tropical rainforest preservation, Ecological Economics 35, 289-302.

Samson, F. and F. Knopf, 1994, Prairie conservation in north america, Bioscience 44, 418-421.

Sauer, J.R., J.E. Hines and J. Fallon, 2003, The North American breeding bird survey, results and analysis 1966-2002, .

Schramm, P., 1990, Prairie restoration: a twenty-five year perspective on establishment and management, , 5–9.

Stone, K., M. Bhat, R. Bhatta and A. Mathews, 2008, Factors influencing community participation in mangroves restoration: A contingent valuation analysis, Ocean & Coastal Management 51, 476-484.

Vermeulen, B., P. Goos and M. Vandebroek, 2008, Models and optimal designs for conjoint choice experiments including a no-choice option, International Journal of Research in

Marketing 25, 94-103.

Vickery, P.D. and J.R. Herkert, 1999, Ecology and conservation of grassland birds of the western hemisphere, Studies in Avian Biology 19.

Vogl, R.J., 1979, Some basic principles of grassland fire management, Environmental management 3, 51-57.

Wang, X., J. Bennett, C. Xie, Z. Zhang and D. Liang, 2007, Estimating non-market environmental benefits of the Conversion of Cropland to Forest and Grassland Program: A choice modeling approach, Ecological Economics 63, 114-125.

Weber, M.A. and S. Stewart, 2009, Public values for river restoration options on the Middle Rio Grande, Restoration Ecology 17, 762-771.

Woodward, R.T. and Y.S. Wui, 2001, The economic value of wetland services: a meta-analysis, Ecological Economics 37, 257-270.

Zhongmin, X., C. Guodong, Z. Zhiqiang, S. Zhiyong and J. Loomis, 2003, Applying contingent valuation in China to measure the total economic value of restoring ecosystem services in Ejina region, Ecological Economics 44, 345-358.

Zizzo, D.J., 2003, Empirical evidence on interdependent preferences: nature or nurture? Cambridge Journal of Economics 27, 867.

4. Selection of Clustered Conservation Areas for Species Relocation, Multiple Species, and Multiple Land Use

Much of the last remnants of suitable habitat areas for many rare, threatened, or endangered species in the U.S. are in the vicinity of military installations. The need for new and conventional training requirements is stronger than before and leads to an increased pressure to manage federal lands by balancing competing objectives and land uses. This chapter consists of three sections each of which develops linear integer programming models to account for various ecological and spatial needs. In section one we introduce formulations for the relocation of multiple populations of a species at risk to clustered conservation areas within a military installation. We apply the models to a dataset related to Gopher Tortoise (GT), a key stone species currently considered ‘at risk’, at Ft. Benning Georgia. In section two we introduce models to allocate land for multiple dependent species. We apply the models to a dataset related to Gopher Tortoise (GT), a key stone species currently considered ‘at risk’, and Gopher Frog, a species dependent on GTs and access to ponds, at Ft. Stewart, Georgia. In section three we introduce models for selecting sites for both conservation and military use. We apply the models to a large-scale real data set for the area surrounding Ft. Benning (GA) and optimally select reserve conservation areas and military areas.

4.1. Introduction

Remnants of suitable habitat areas for many rare, threatened, or endangered species in North America are on or near military installations in the U.S. (Stein and Benton 2008). Figure 4.1 shows that Department of Defense (DoD) lands have the highest density of and second highest distribution of endangered and imperiled species amongst all the Federal land management agencies. While some habitat deterioration may have been caused by military training, it is often argued that the military training and testing actually prevents destructive urban and agricultural development (Orth and Warren 2006). Besides isolation of the lands from alternative economic uses, the Department of Defense allocates a significant amount of human capital and land for conservation efforts toward protecting and managing wildlife habitat in and around military installations. In 2006, the DoD spent $4.1 billion on environment related expenses of which $1.4 billion was for environment restoration and $204.1 million was for conservation (Benton et al. 2008). On the other hand, new and conventional training requirements are increasing the importance of military lands and setting aside some land for conservation purposes may lead to inadequate training and testing. This increases the pressure to manage military lands in the best possible way to balance these competing objectives and land uses. As an alternative to costly arrangements, such as purchasing land, acquisition of property rights, and sharing land with other agencies, effective utilization of the existing lands for conservation and military purposes can be accomplished by designing an optimum landscape that places conservation and military training areas in a desirable spatial configuration. This issue is the main motivation of this paper. We explore alternative optimum conservation reserve designs by incorporating various ecologically important spatial considerations along with military training requirements in a mathematical modeling framework.

4.2. Literature Review

Our approach to solving the relocation problem is similar to that involved in the design of “reserves” for protection of certain sensitive species, where the use of mathematical models goes back to the 1980’s (Kirkpatrick 1983). The use of the term “reserve” is not entirely appropriate, however, when dealing with conservation efforts on military installations where protection of certain species and considerations for their management are always subject to mission requirements and Congressional authority. Therefore, we use the term “Conservation Management Area (CMA)” with regard to the application and the term “reserve” with regard to the theoretical modeling analysis.

Mathematical programming methods, in particular linear integer programming, have been used widely in the literature of biological conservation and reserve design. Initial studies used mostly heuristic methods for this purpose (Margules and Pressey 2000; Vane-Wright et al. 1991; Nicholls and Margules 1993; Pressey et al. 1993; Pressey et al. 1997). Later, formal optimization models were introduced to either determine a least-cost site selection that provides suitable habitat to each and every target species (Underhill 1994; Possingham et al. 2000; Rodrigues and Gaston 2002) or maximize the number of species covered subject to a budget or area limitations (Ando et al. 1998; Camm 1996; Church; et al. 1996). In its simplest form, the reserve design problem is stated as selecting a minimum number of habitat sites that contain populations of a specified set of species, or maximizing the number of species that can be protected under a conservation budget constraint or area limitations. Both problems are formulated as linear integer programs (IP), being special cases of the prototype ‘set covering’ problem and the ‘maximal covering’ problem.

In this paper we use the first approach; we want to select a minimum number of sites, clustered into CMAs, that together meet a minimum protected population requirement Mathematically, Given *L* sites, where site *l* provides habitat services to p_{lm} individuals of species *m*, and a total protected population requirement of tp_m for species *m*, the basic set covering problem would take the form:

$$(1.1) \quad \text{Minimize} \quad \sum_{l} S_l$$

such that:

$$(1.2) \qquad \sum_{l} p_{lm} S_l \geq tp_m \quad \forall \text{m}$$

$$(1.3) \qquad S_l = 0,1 \qquad \forall l$$

In the above model S_l denotes a binary variable where S_l = 1 indicates that site *l* is selected as part of the CMA, and S_l = 0 otherwise. With no further constraints the solution is simply the smallest set of sites that individually provide the greatest habitat services.

Typically, this type of optimum site selection model results in highly sparse and dispersed reserve configurations whereas spatial coherence of the selected reserve sites is in general desirable for effective functioning of the reserve system and species long-term survival. Recognizing this deficiency, several integer programming models have been developed particularly in the past ten years to incorporate various forms of spatial considerations, such as reserve connectivity, compactness, fragmentation, etc. (Williams and ReVelle 1998; Cova and Church 2000; Nalle et al. 2002; Önal and Briers 2002, 2003, 2005; Cabeza 2003; Cerdeira et al. 2005; Cerdeira and Pinto 2005; Önal and Wang 2008; Tóth et al. 2009). For a review of these spatial optimization studies refer to Williams et al. (2005). This type of consideration generally requires a much more complex mathematical formulation and large-scale models.

The models presented in this chapter consider a grid partition which comprises of square land parcels[40]. Each parcel (site) is assumed to be an independent decision unit. When selecting sites to conFigure 4.a compact CMA the locations of individual sites relative to other selected sites and their contributions to the conservation of GT are taken into account simultaneously. More specifically, we require a CMA to be formed by a set of sites packed (clustered) around a ‘central site’, as shown in Figure 4.2. Figure 4.2.a depicts a scattered CMA while Figure 4.2.b shows a clustered CMA where C_1 indicates the central site and the S_i‘s indicate the sites selected as part of the CMA. The problem is then to determine the central site of each CMA and assignment of individual sites to the CMA in an endogenous way while satisfying the conservation requirements and considering alternative spatial criteria in cluster formation[41].

4.3. General Methods and Data

In section 4 titled, “Optimum Selection of Clustered Conservation Areas for Species Relocation” we address the need to relocate species when new training sites are created within a military installation. We introduce linear integer programming formulations for the relocation of multiple populations of a species at risk to clustered conservation areas within the boundaries of a military installation. We present a basic clustered relocation model and extend the model

[40] The square-cell assumption is not restrictive. The approach developed here can be applied to other geometric forms, such as triangles, rectangles, polygons, or even irregular forms.
[41] This model is an extension of classic p-median problem (Garfinkel et al. 1974). Similar models for clustering have been used previously in the literature of reserve design, business districting and political districting [Önal and Briers 2005, Williams et al. 2005].

to minimize the distances of relocation, and to impose meta-spatial clustering on the selected areas. We introduce two methods for meta-spatial clustering, using a constraint and using a multi objective function. We apply the models to a dataset related to Gopher Tortoise (GT), a key stone species currently considered ‘at risk’, at Ft. Benning Georgia and analyze the results.

In section 5 titled, “Optimal Selection of Conservation Lands for Dependent Species: The Case of Gopher Tortoise and Gopher Frog at Ft. Stewart, GA” we demonstrate the use of linear integer programming formulations to identify the sites for forming clustered biodiversity management areas within the boundaries of a military installation. We present a basic clustered site selection model and extend the model to include a secondary species. We apply the models to a dataset related to Gopher Tortoise (GT), a key stone species currently considered ‘at risk’, and Gopher Frog, a species dependent on GTs and access to ponds, at Ft. Stewart, Georgia.

In section 6 titled, “Optimum Selection of Land for Conservation and Military Use” we create land use allocation models that incorporate multiple land use. Most of the recent work in reserve design has focused on one specific land use, namely species conservation. In many cases, however, it is important to simultaneously consider multiple land use within a landscape. We introduce a multiple land use reserve design model that includes spatial and ecological criteria and highlight two extensions: a multiple land use meta-clustering model and a multiple land use proximity-to-roads model. A large-scale real data set for the area surrounding Ft. Benning (GA) is used to optimally select reserve conservation areas and military areas. We believe this approach will contribute to the ability of land managers at installations to extract more overall utility from military installation training and testing areas.

The land use decision problem described above can be solved using linear integer optimization methods. The specific problem may be different from one case to another depending on unique characteristics of each installation in terms of military training and environmental/ecological needs.

In all three sections the data manipulation and model implementation was conducted using readily available software as presented in Figure 4.3. Habitat suitability and military training information was obtained from personnel at Ft. Benning and Ft. Stewart with the assistance from CERL research scientists. The data was extracted into grid shape files using GeoDa and ArcGIS and imported into GAMS using Excel. The results were computed in GAMS and mapped using ArcGIS. The three sections below use three different data sets, therefore the data is described in more detail within each of the sections.

Figures

Figure 4.1.a: Density of Species on land managed by Federal agencies*

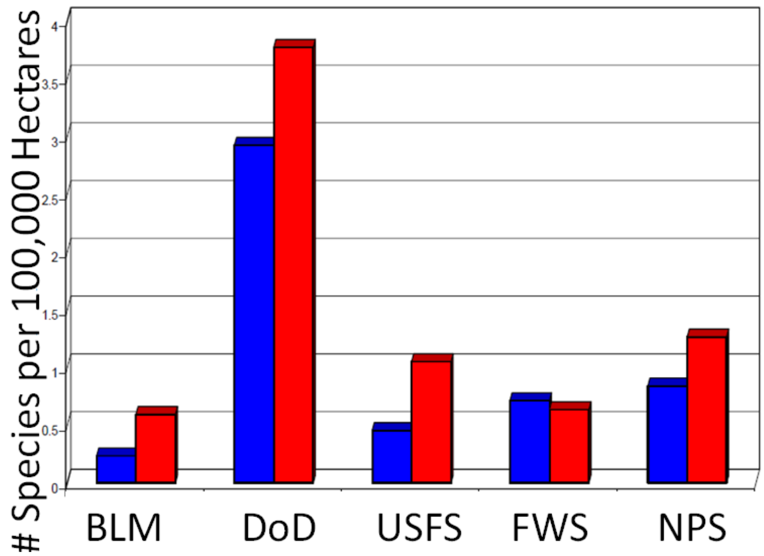
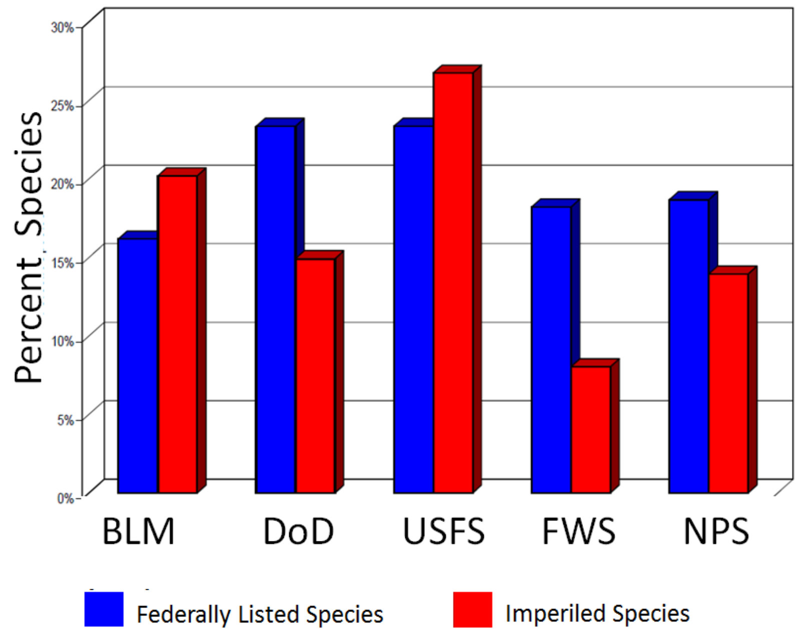


Figure 4.1.b: Distribution of Species on land managed by Federal agencies*



BLM – Bureau of Land Management
DoD – Department of Defense
USFS – United States Forest Service
FWS – Fish and Wildlife Service
NPS – National Park Service

*Figures based on Stein and Benton (2008).

Figure 4.2: Example of Clustered Site Selection

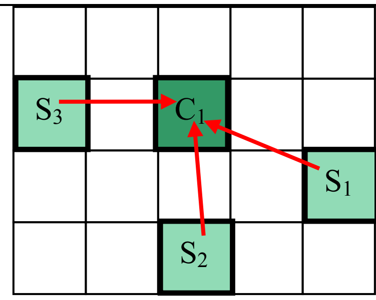


Figure 2.a. Scattered Selection

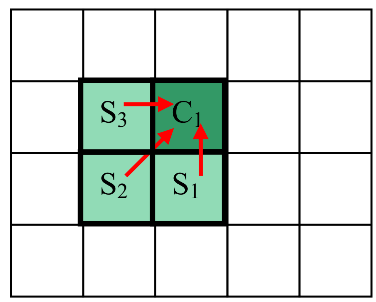
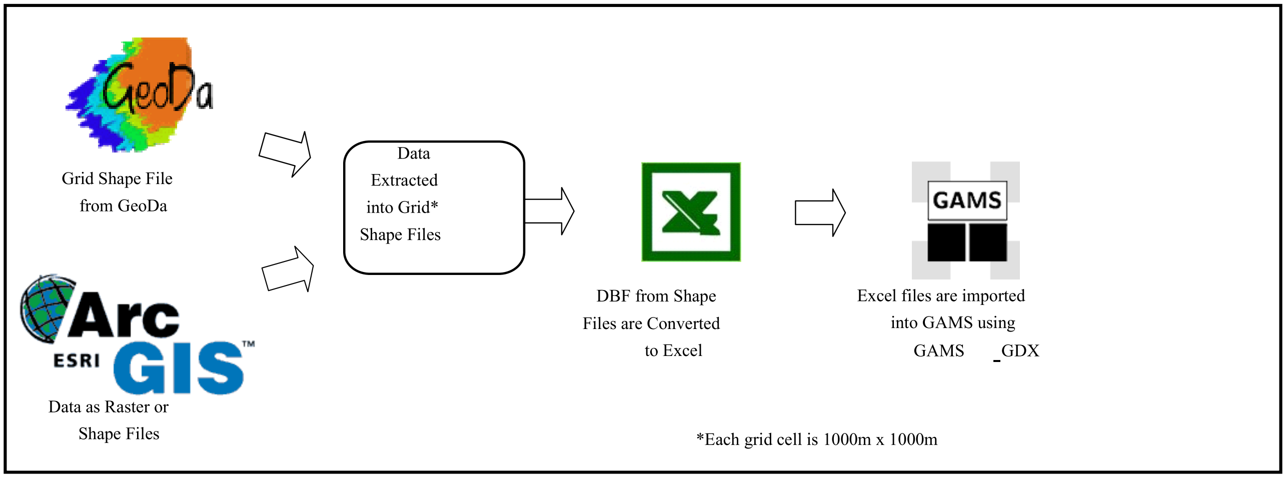


Figure 2.b. Clustered Selection

Figure 4.3: Data Processing and Software



4.4. Optimum Selection of Clustered Conservation Areas for Species Relocation

Much of the last remnants of suitable habitat areas for many rare, threatened, or endangered species in the U.S. are in the vicinity of military installations. The need for new and conventional training requirements is stronger than before and leads to an increased pressure to manage federal lands by balancing competing objectives and land uses. This paper introduces linear integer programming formulations for the relocation of multiple populations of a species at risk to clustered conservation areas within the boundaries of a military installation. We present a basic clustered relocation model and extend the model to minimize the distances of relocation, and to impose meta-spatial clustering on the selected areas. We introduce two methods for meta-spatial clustering, first using a constraint and second using a multi objective function. We apply the models to a dataset related to Gopher Tortoise (GT), a key stone species currently considered ‘at risk’, at Ft. Benning Georgia and analyze the results.

4.4.1. Introduction

As we look to the future of creating protected habitats, relocation of species becomes an important component in identifying the optimal reserve areas. The growing importance of species relocation is driven by two factors. First, given the increasing expansion of human dominated landscapes it becomes necessary to relocate endangered and at-risk species from existing habitat areas to new and suitable protected habitats. Second, the recent research that analyzes the impact of climate change on critical habitat areas show that climatic and atmospheric changes affect species distributions in their current geographic ranges (Halpin 1997; Hughes 2000; McCarty 2001; Walther et al. 2002; Root et al. 2003; Burns et al. 2003; Araújo et al. 2004; Martinez-Meyer 2005; Saunders et al. 2007; Lawler 2009). Therefore, identifying new suitable conservation reserves and protected areas becomes necessary.

The reserve design models presented in the reserve design literature have mostly focused on choosing the optimal land area given existing species distributions and have not incorporated species relocation as a criterion. The few exceptions presented in the literature review either focus on the ecological and genetic aspects of species relocation and reintroduction or present models that include detailed population dynamics both of which are unnecessary for the current problem. Further none of the relocation models incorporate relocation distances as a criterion. In this paper, we present a reserve design model and formulate the problem of relocating endangered or at-risk species to a new protected area given ecological and spatial requirements. The model identifies the land parcels to be set aside as conservation areas given that some of the individuals will be relocated from their current habitat areas. The model aims to minimize the relocation distances, which would minimize the movement costs and more importantly minimize the stress placed on the individuals being relocated.

We present an empirical application of the model to select the best conservation management areas for Gopher Tortoise (GT, *Gopherus Polyphemus*) within the boundaries of a military installation, Ft. Benning, GA.[42] Gopher Tortoise is a threatened species[43] and although there are multiple populations in Mississippi, Alabama, Georgia and Florida, the last century has seen a nearly 80% decrease in those populations (BenDor et al. 2009). Ft. Benning includes a significant population of GT's and several other species whose habitat areas are currently being managed for protection. However, the installation is currently undergoing an expansion of the training mission which increases the demand for land used for training and needs to convert some of the existing GT habitat areas to military training areas. Therefore, relocation of the affected populations to optimally selected conservation areas within the installation is a necessity. This is an economically efficient and ecologically sound option and would achieve the conservation goals without the need to purchase new lands. Though the relocation models presented below are applied to GT's, the models are applicable to relocating any terrestrial species.

[42]Suitable habitat areas for many rare, threatened, or endangered species in North America are on military installations in the U.S. The number of endangered and threatened plant and animal species found on Department of Defense (DoD) lands is almost the same as the number of species found on the lands managed by US Forest Service (USFS) and significantly higher than the number of species on the lands managed by other federal agencies such as National Park Service (NPS), US Fish and Wildlife Service (USFWS) and Bureau of Land Reclamation (BLM) (Flather et al. 1994; Flather et al. 1998). The Department of Defense (DoD) actively manages wildlife habitat in and around military installations. In 2006, the DoD spent \$4.1 billion on environment related expenses of which \$1.4 billion was for restoration and \$204.1 million was for conservation (Benton, et al. 2008)

[43]As listed by the US Fish and Wildlife Service for Louisiana, Mississippi, and west of the Tombigbee and Mobile Rivers in Alabama. The Department of Defense (DoD) considers to be a Species at Risk (SAR) with regard to other GT locations (BenDor, et al. 2009).

4.4.2. Literature Review

Even though reserve design formulations have expanded to include many spatial and ecological criteria, the relocation problem has not been addressed in the reserve design literature. Given the increasing threat to existing protected areas and endangered species habitats from expanding human activities and the shifts in species distributions due to climate change the optimal relocation of endangered species is growing in importance. Our extensive search of the reserve design literature resulted in five papers that use mathematical optimization techniques to solve an optimal species relocation problem[44]. Kostreva (1999) presents four general nonlinear models based on the integer knapsack problem to analyze the relocation decision problem based on genetic diversity of the species under consideration. Their model is focused on the genetic properties of the species population and the paper is aimed at highlighting the computational techniques of solving complex knapsack problems. The main contribution of their paper is not to the ecological and reserve design literature but rather more to the mathematical programming literature. Further, the problem at hand requires modeling the spatial configurations of GT habitats rather than the genetic diversity of the GT population, therefore the models presented in Kostreva (1999) are unnecessarily complex both in terms of modeling and computational complexity. Tenhumberg et al. (2004) present an optimal relocation model that is focused on the optimal reintroduction of captive individuals from an endangered species. They address the problem using meta-population models of a captive and wild population and identify optimal capture and release strategies and apply the model to the globally endangered Asiatic wild horse. The model presented by Tenhumberg et al. (2004) is not

[44] We thank an anonymous referee for calling our attention to two of the papers.

directly applicable to the problem at hand as the current problem does not involve captive breeding and release of GT populations. We are interested in identifying the optimal allocation of land to be set aside as protected areas with the addition that some of the individuals will be relocated from areas threatened by human expansion and/or climate change. Lubow (1996) develops an optimal translocation strategy given stochastic dynamic considerations. Lubow applies his model to a hypothetical setting that has two reserves. As Lubow mentions in the paper, the applicability of stochastic dynamic programming (SDP) is severely restricted by the "curse of dimensionality" and computational complexity typically grows exponentially in the number of sites. Therefore, it is not feasible to apply dynamic programming to solve the problem at hand which requires relocating individuals between hundreds of possible sites. Haight et al. (2005) present an optimization model to solve various translocation problems where population growth and future funding are uncertain. Their model does not include spatial considerations and is therefore inapplicable to the problem at hand. Bevers et al. (1997) present a dynamic spatial optimization model of prairie dog colonies for black footed ferret recovery that includes multiple time periods and very detailed ecological considerations including population growth, persistence, dispersal and carrying capacities. Bevers et al. (1997) does not include relocation considerations. Thought their model could be modified to include relocation considerations, their model is unnecessarily complex for the present task as it requires modeling persistence and dispersal of GT populations. The problem at hand does not require an explicit model of GT population persistence and dispersal since the GT populations have a limited range and the GT life cycle is longer than that of the black footed ferret. Therefore none of the existing relocation models are directly applicable to the current research problem.

In this paper, we present a static integer programming model that takes the relocation of species into account when designing a conservation reserve by selecting the most suitable sites from among hundreds of candidate sites. The model considers species relocation at a population level (as opposed to an individual level) and it is spatially explicit with regard to compactness of the selected sites and minimization of the relocation distances.

4.4.3. Methods

The procedures and algebraic details of the models are described explicitly below. We denote the set of all sites by *L* and denote individual sites by $k, l, j \in L$. Site selection and assignment to a CMA is represented by a binary variable X_{lk}, where X_{lk} =1 if site *k* is selected and belongs to the CMA centered at site *l* and X_{lk} =0 otherwise. Note that by construct X_{ll} =1 for all central sites *l*, i.e. the central site of each CMA must belong to that CMA. We also note that sites in the most heavily used military training areas (existing or new) are not considered for inclusion in any CMA, therefore we set X_{lk} =0 if site *k* is part of a training area. The symbol d_{lk} denotes the distance between site *l* and site *k*, and e_k denotes the existing population of GT in site *k*. The number of CMAs to configure is denoted by *n*, which is specified exogenously but varied when designing alternative optimal configurations. Each CMA is required to sustain a minimum GT population, denoted by *p*. Finally, the total GT population in all the selected areas is represented by *tp*.

4.4.3.1. Base Model

We first address the problem of constructing *n* compact CMAs, each covering a minimum sustainable GT population and collectively covering a desired GT population within the available budget. Here we define compactness of a CMA as the overall 'closeness' of all sites in it. We measure this by the sum of distances from all sites to a central site in each cluster, which must be minimized to the extent possible[45]. An algebraic model that serves this purpose, which will be referred to as the '*Base Model*' from here on, is given below.

$$\text{Minimize} \quad \sum_{l} \sum_{k} X_{lk} * d_{lk}$$

<u>Objective Function:</u> Sum of distances to centers

s.t.:

<u>Constraints:</u>

i) $\sum_{l} X_{ll} = n$ — i) Total number of CMAs = n

ii) $\sum_{l} X_{lk} \leq 1 \quad \forall k$ — ii) Each site can belong to at most one CMA

iii) $\sum_{k} X_{lk} * e_k \geq p \quad \forall l$ — iii) Minimum population for each CMA

iv) $\sum_{l} \sum_{k} X_{lk} * e_k \geq tp$ — iv) Minimum total population

v) $\sum_{k} X_{lk} \leq m X_{ll} \quad \forall l$ — v) Site assignment can be done only if site l is a center (X_{ll} = 1)

vi) $\sum_{l} \sum_{k} X_{lk} * c_k \leq b$ — vi) Total cost must not exceed the available budget

$$X_{lk} = 0,1 \quad \forall l,k$$

Binary restrictions for site selection variables (1 if site k belongs to a reserve centered at site l, 0 otherwise)

The objective function involves the distances from individual sites in each CMA to the 'center' of that CMA, which in turn is summed over all CMAs. Constraint i) ensures that n CMAs are created. Constraint ii) states that each site can belong to at most one CMA centered at some

[45] Compactness is not a well-defined concept (Young. 1988). Note that the absolute value of the compactness measure defined here may not mean much just by itself, rather it has to be considered together with the size of the reserve (number of sites involved). This is because a reserve with only a few distant sites may have a smaller total distance value than a reserve with too many tightly packed sites, whereas in practice the latter should be considered more compact. Although not being fully satisfactory, this definition well serves the specific purposes of the present study. Minimizing the total distance typically results in a circular and connected reserve configuration. An alternative would be to choose a contiguous reserve configuration. Contiguous reserve design models can result in connected components that are not compact. Given that GTs are a ground dwelling species compactness is necessary, therefore we use compact meta clustering formulations. See (Önal and Wang. 2008)and (Tóth, et al. 2009)for an exact formulation of contiguity in reserve design formulations.

site l. Constraint iii) requires that each CMA supports a population that meets or exceeds the minimum sustainable size[46], while constraint iv) ensures that all CMAs collectively support a desired total population. Constraint v) implies that if site k is selected and assigned to the central site l, i.e., X_{lk} =1, then a CMA centered at site l must be formed, i.e. X_{ll} must be 1, otherwise we have X_{lk} =0. The symbol m denotes an arbitrarily specified large number, which implies that if site l serves as the center of a CMA, then up to m sites can be assigned to that CMA. Finally constraint vi) is a budget constraint where c_k is the cost of selecting site k as part of the reserve and b is the total budget available for the conservation purpose.[47] We note that the sites that are part of the existing and proposed intensive use military training areas are not eligible for selection, therefore for all such sites we set X_{lk} =0.

The above base model does not incorporate the relocation distances. We address this issue below and present alternative models to identify the most suitable habitat areas that should be set aside as designated GT habitats.

4.4.3.2. Base Relocation Model

Over the next few years a significant amount of new land will be utilized as training areas within Ft. Benning. Figure 4.4 and Figure 4.5 display the nature of the problem. The current military training areas are shown in Figure 4.4.a, and the planned intensive training areas to be added are given in Figure 4.4.b. As can be seen in Figures 3.b and 4.a, the new military training areas contain many GT populations. Therefore, those populations have to be moved to new habitat

[46] This constraint can also be expressed in terms of a minimum number of sites if the effectiveness of conservation effort is related to the reserve size.
[47] The cost can either be just the physical cost of the conservation process or it can include the opportunity cost of lost training depending on the scenario. The budget constraint was not considered in the remainder of the analysis since in the present application cost was not a consideration.

areas that will be selected from among the areas in Figure 4.5.b that are not planned for additional training uses. The relocation model seeks to select the best CMAs and determine optimal relocation of the existing GT populations that are within the planned new military training areas. The selection of those parcels must be done in such a way that: i) the new protected CMAs must be as compact as possible; ii) each CMA must be large enough to include a sustainable GT population and all CMAs collectively accommodate the GT populations currently located within the planned expansion areas; and iii) the existing populations are moved by minimal distances. The first two criteria are met in the Base Model formulation. The last criterion aims to maximize the survival likelihood of the GT populations that are relocated with the assumption that if the relocation distances are small the GT populations are more likely to adapt to their new environment[48].

In addition to the notation used earlier we define a new binary variable Y_{lj}, where $Y_{lj} = 1$ if the GT population in site j is moved to the CMA centered at site l.[49] We note that the entire population in a given site is moved together to a new area, i.e. no partial relocation is allowed. We first introduce a Relocation Model which solves the relocation problem without incorporating movement distances and then expand the model to include relocation distances. The following model, which we call the Base Relocation Model, solves the optimal site selection and relocation decisions:

---

[48] The relocation distances in the model can be replaced with costs attributed with movement. Although relocation (travel) costs were not considered in this application, it can be a significant consideration in many other applications. The model can be easily modified to directly minimize the travel costs by adding $X_{lk}d_{lk}c_{lk}$ to the objective function where c_{lk} is the travel cost between site l and site k.

[49] variables Y_{lj} are defined only for sites that are predefined as new military training areas and cannot be used for CMAs, i.e. *j* identifies sites that are identified as new military training areas.

$$
\begin{aligned}
&\text{Minimize} \quad \sum_l \sum_k X_{lk} * d_{lk} \\
&\text{s.t.: i)} \quad \sum_l X_{ll} = n \\
&\text{ii)} \quad \sum_l X_{lk} \le 1 \quad \forall k \\
&\text{iii')} \quad \sum_k X_{lk} * e_k + \sum_j Y_{lj} * e_j \ge X_{ll} * p \quad \forall l \\
&\text{iv')} \quad \sum_k X_{lk} * e_k + \sum_j Y_{lj} * e_j \le \sum_k X_{lk} * cc_k \quad \forall l \\
&\text{v')} \quad \sum_l \sum_k X_{lk} * e_k + \sum_l \sum_j Y_{lj} * e_j \ge tp \\
&\text{vi)} \quad \sum_k X_{lk} \le m X_{ll} \quad \forall l \\
&\text{vii)} \quad \sum_j Y_{lj} \le m X_{ll} \quad \forall l \\
&\text{viii)} \quad \sum_l Y_{lj} = 1 \quad \forall j \\
&X_{lk}, Y_{lj} = 0,1
\end{aligned}
$$

Only the new or revised constraints are described below.

iii') The sum of the existing population and the population moved to a CMA is greater than the minimum viable population for each CMA.

iv') The total (existing plus relocated) population in a CMA is less than the total carrying capacity of the sites in that CMA.

v') The total (existing plus relocated) population in all CMAs is greater than the total target population to be protected.

vii) GT's are only moved to sites that belong to selected CMAs.

viii) All GT's in sites that will be used by the military are moved.

Several of the constraints given above have already been discussed as components of the Base Model; therefore we describe only the new constraints here. Constraint iv') ensures that for each CMA, the sum of the existing GT population and the new GT populations moved to that area does not exceed the carrying capacity of that CMA, which is the sum of the carrying capacities of individual sites (denoted by cc_k) included in that CMA. In this particular application, the habitat suitability of each site is represented by an index created from the GT suitability map (Figure 4.5.b). Similarly, constraints iii') and v') are revised forms of iii) and v) in the Base Model. Constraint vii) states that the GT population in site j can be moved to a CMA with center at l (i.e. Y_{lj} = 1) only if such a CMA is indeed formed (i.e. X_{ll} = 1), otherwise we must have $Y_{lj} = X_{ll} = 0$. Constraint viii) ensures that the entire population in each new military training site is moved to one and only one CMA. The last constraint was added because GT's are believed to have social interactions; therefore keeping the entire community together is believed to reduce the negative impact of relocation.

4.4.3.3. Minimum Distance Relocation Model

We extend the above model by adding a movement distance term to the objective function as:

$$\text{Minimize} \quad \sum_{l}\sum_{k} X_{lk} * d_{lk} + \beta \sum_{l}\sum_{m} Y_{lm} * d_{lm}$$

The objective function consists of two components. The first part is the sum of distances from sites in the selected CMAs to the centers of those CMAs, as in the Base Relocation Model. The second term is the total distance that all GT populations are moved. The parameter β is the objective function weight that specifies the importance of the total relocation distance component in the objective function relative to the overall compactness of the reserve. We present an analysis of the sensitivity of this objective function weight in the results section. It may or may not be possible to minimize these two terms at the same time. This model, which we call the Minimum Distance Relocation Model, explicitly considers the trade-off between CMA compactness and the relocation distances in a unified framework and determines a compromise solution.

4.4.4. Data

The current and future military training areas were obtained as raster files from Ft. Benning and are shown in Figure 4.4.a and 3.b. The habitat areas suitable for GT were obtained as raster files from the National Biological Information Infrastructure (NBII) (Elliott et al. 2003). The above raster files were converted to ESRI shape files using ARC GIS 9.2. The resulting shape file is shown in Figure 4.4.b. A 40x40 grid file, where each grid was 900m by 900m, was created using

GeoDa and the grid shape file was spatially joined with the above shape files using spatial join tool in ARC GIS. The spatial join gives the grid file the attributes of the shape file. To ensure that each grid cell represents a density of the original data, the "sum" option was used when joining the GT burrow data and the habitat suitability data.

The grid cell values for Figure 4.4 are specified as binary values (grid cell value = 1 if cell includes a base area or a planned expansion area). The grid cell values for Figure 4.5 are given as an index. For Figure 4.5.a, each grid cell value is the sum of the number of observed GT burrows within the grid cell, where the index ranges from 0 to 350. For Figure 4.5.b, the grid cell value is the sum of the suitable points (the GT suitability raster map was converted to point shape file) within the grid cell. The suitability index for Figure 4.5.b ranges from 0 to 864. It is necessary to convert the habitat suitability index obtained from the NBII data into a GT carrying capacity value. The GT population density parameter, δ, is used with the habitat suitability index to calculate the carrying capacity of GTs for each grid cell.[50] Each one-hectare land parcel can support between 2 to 4 GT's (Ashton and Ashton 2004). This is equivalent to supporting between 180–360 GT per grid cell at the 900m x 900m resolution. Therefore, the density parameter is set to 0.5 in the empirical analysis[51].

The ecological suitability values obtained from the NBII raster data for GT suitability for GA reflects the present suitability of land for GTs. The model as formulated can be used to identify areas for relocation due to potential climate change impacts on habitat suitability given

[50]The population density parameter δ is introduced into the model by multiplying the carrying capacity value, c_k, by δ. We incorporate this parameter into the model to allow the user to incorporate site specific information about the carrying capacity of the land.

[51] The number was chosen to relate the observed GT populations with the carrying capacity map and we conducted an analysis of the sensitivity of this parameter. A lower value for δ results in more land being needed to meet the minimum population criteria and a higher value for δ leads to less land being necessary to meet the minimum population criteria.

data about future land suitability. The difficulty here would lie in acquiring expected land suitability information, but as mentioned in the literature review there is a growing literature trying to predict land suitability for various species in the future. The relocation model can use these expected values of site suitability and generate probabilistic reserve site selections based on the probabilities of ecosystem changes in the future.

4.4.5. Results and Discussion

This section presents the results of the base relocation model and the minimum distance relocation model. All models were solved using GAMS/CPLEX version 21.6 on a PC with an Intel Core 2 Duo processor and 2 GB of RAM running Windows XP. The total population of GTs that needs to be relocated is estimated to be at least 1800. This is based on the actual burrow counts in the areas that will be allocated exclusively to military use (see Figure 4.5.b). Because there are existing GT populations in the potential CMAs we consider an overestimate of the total number relocated for the total minimum population size that the entire conservation area should hold after relocation (the parameter *tp*). Here we assumed that the final total population in all CMAs (including the existing GT populations and the relocated populations, i.e. the parameter *tp*) is at least 4000[52]. In theory, the GT populations that are currently located in the planned military expansion areas can be moved to a single large CMA or multiple smaller CMAs. We require the CMAs to be as compact as possible and assume that sites belonging to the intensive-use maneuver zones are not eligible for selection. The model is solved with various parameter specifications for the number of CMAs (i.e., *n*). The reasons for specifying

[52]Four thousand is a rough estimate of the 1996-8 total population of tortoises on Ft. Benning based on a total burrow count, but it needs to be noted that we use this number to illustrate the model and not as a realistic indication of GT management at Ft. Benning.

more than one CMA are three-fold[53]. First, we may want to separate the relocated GT population into smaller populations, each being located in a different part of the installation, to safeguard them against potential diseases that may occur in a protected area and spread to the other areas. Second, one big CMA requires movement over large distances of several populations located in different parts of the new training zones, which might create a more challenging adjustment problem particularly for the populations relocated to distant areas. Third, setting aside one large conservation area reduces the flexibility for the military when further expansion of training areas is needed in future. These problems can be alleviated or reduced by designing multiple small conservation areas.

In all of the runs described below the minimum population for each CMA, *p*, was specified as 750[54] and the minimum total population, *tp*, was specified as 4000. Both models were solved for one, two, three and four CMAs. These parameter values are specified to illustrate the workings of the models and demonstrate the trade-offs between different spatial criteria.[55]

4.4.5.1. Base Relocation Results

The Base Relocation Model results, without spatial considerations other than compactness of

[53] The optimal number of reserve sites has been analyzed in the reserve design literature. A recent paper (Zhou and Wang. 2006) analyzes the optimal number of reserve using a meta-population model.

[54]The minimum sustainable population size for Gopher Tortoises varies considerably; See Styrsky et al. 2010 for an analysis of GT population threshold levels. In this study we use 750 to require the model to select multiple sites for each CMA. For very low minimum population values each CMA consists of only one or two sites at the current resolution and this prevents the analysis of the spatial tradeoffs. Low minimum population values can be analyzed by obtaining higher resolution data and conducting the analysis with a finer grid scale.

[55]It is important to emphasize that this study is focused on presenting methods that can take relocation considerations into account using a potential real world application and not as a realistic indication of GT management plans at Ft. Benning

the selected CMAs, are shown in Figure 4.6 for 1, 2, 3 and 4 CMAs. Comparing the results in Figure 4.6 with the suitability map given in Figure 4.4.c illustrates that the Base Model simply selects from among the most densely packed and best available sites to form contiguous and compact CMAs. The optimal solution with one large conservation area (Figure 4.6.a) shows that this area would be located at the southeast corner of the installation. However, the compactness of the CMA is poor; the selected sites (16 total) are meandering in shape. This result is driven primarily by the fact that the model is forced to choose one cluster of habitat sites and the only available good quality sites that are not currently populated heavily by GT are in that part of the installation. The good quality sites in other parts of the installation are not in the solution due to three reasons: i) those sites are under extensive military use, ii) a high density of GT currently inhabiting the sites would not allow relocating new GT's into those areas, or iii) those sites are located far apart from each other.

For the two-CMA case the model chooses two clusters with four and eight sites, respectively (Figure 4.6.b). The three-CMA case selects a total of ten sites (Figure 4.6.c), and the four-CMA case requires a total number of 11 selected sites (Figure 4.6.d). Unlike the one big CMA scenario, the two, three and four-CMA configurations comprise of compact clusters of sites since instersite distances are accounted for each cluster separately, rather than the distances between all selected sites, which allows the model to choose closely located sites from multiple locations. Based on these results, we may conclude that if the size of the total area to be CMAs is a concern, forming three CMAs, two located in the southwest and one located in the north-central areas, would be the best strategy as it involves the minimum number of sites (=10).

4.4.5.2. Minimum Distance Relocation Results

The results of the minimum relocation distance model are shown in Figure 4.7. The optimal solution with one large conservation area (Figure 4.7.a) shows that this area would again be located at the southeast corner of the installation (although slightly different from the solution displayed in Figure 4.6). The compactness of this CMA is even poorer, where among the 16 selected sites one site is disjoint from the other sites. Besides the reasons that were discussed above, minimizing the relocation distances as an additional consideration works against the primary objective (i.e., compactness) when only one cluster is being selected.

The results for two CMAs are shown in Figure 4.7.b. The change in the CMA locations is dramatic when compared to Figure 4.6.b. Incorporating the relocation distances in the objective function (besides compactness) moves the selected clusters towards the top center and bottom center of the installation. None of the southeastern sites was chosen; instead 8 sites in the north and 11 sites in the south are selected to form the two CMAs. Compared to Figure 4.7.a, the factors behind this selection are: i) minimizing the movement distances makes the sites in the those two locations more attractive than before because they are closer to the current GT habitats; ii) as the number of CMA's being considered increases the model is able choose smaller CMA's in higher quality areas.[56] This was not possible in the previous case (Figure 4.7.a) which required finding sites in one area, which forces the model to select some subpar sites.

The results for three and four conservation clusters are shown in Figure 4.7.c and Figure

[56] As more CMAs are considered each CMAs has to contribute less towards the total population (if only one CMAs is being chosen then that CMA would need to accommodate a population of 4000, whereas if two CMA's are being chosen, then one CMAs could accommodate population of as little as 750)

4.7.d. Once again a dramatic change occurs in the CMA configuration compared to the results in Figure 4.6.c and Figure 4.6.d. For the three-CMA scenario, the model chooses 17 sites which are centrally located and relatively close to the area where GT's are to be relocated from. The model does not choose any site from the highly suitable south-east corner, since the movement distances to those sites are higher. For the four-CMA, scenario, the model chooses a total of 16 sites, again among the centrally located sites. The four sites in the southeast (best ones from the solution with one large CMA cluster) form a CMA in that area, which is much smaller than the first solution however, while three small CMAs are formed in the northeast, central and southern parts of the installation. This result is driven again by the habitat quality and relaxed CMA size limitation as well as the preferred compactness property and the aim to reduce the total relocation distance. A clear distinction between the CMAs seen in Figure 4.7 and the ones in Figure 4.6 is that the four CMAs selected without consideration of relocation distances are much more compact. This is an intuitive and expected result, indicating the trade-offs between competing objectives, namely relocation distances and compactness of individual CMAs. Another evident distinction between the two sets of CMA configurations in Figures 5 and 6 is that the relocation model selects larger clusters of sites compared to the model that considers compactness only. This result is driven jointly by the relocation distances and habitat qualities of individual sites. More specifically, consideration of relocation distances favors the sites that are closer to the current GT habitats, which are (in this data set) of poorer quality than the remote but good quality sites shown in Figure 4.6. It should be noted that the weights assigned to the CMA compactness and total distance of relocation objectives heavily influence the outcomes. Assigning a higher weight to compactness results in more compact and usually contiguous, CMA configurations; on the other hand, placing a higher weight to the relocation distance shifts the CMA locations towards the planned military training areas, which typically reduces the compactness of individual CMAs. We present a detailed analysis of the objective function weights in the next section.

4.4.5.3 Sensitivity Analysis of the Objective Function Weights

The results from multi-objective optimization models are sensitive to the choice of weights used in objective function. The results discussed above (Figure 4.6 and Figure 4.7) used equal weights for both components of the objective function (β=1). Therefore, in an effort to analyze the impact of the weight and the tradeoff between the clustering component and the relocation distance component we conducted a sensitivity analysis of the weights by systematically changing the relative weights of each component.[57]

Figure 4.8 presents the tradeoff between clustering and relocation distances for n = 1, 2, 3, 4. The data corresponding to Figure 4.8 is given in Table 4.1. Figure 4.8 and Table 4.1 illustrate that increasing the weight on the relocation distance component of the objective function decreases the relocation distance. At the same time this leads to a decrease in the compactness of the selected sites. For a given number of CMAs, Figure 4.8 illustrates an efficiency frontier. The efficiency frontier grows when the model is required to select a higher number of CMAs. This result is to be expected since a larger number of CMAs allows for each CMA to be smaller and located in areas with high GT habitat suitability that are closer to existing GT areas, which increases the compactness and decreases the relocation distances.

Table 4.1 also highlights that increasing the weight on the relocation distance

[57] The sensitivity analysis used values for beta ranging from 0.001 to 1000

component typically leads to an increase in the total number of sites selected for the CMAs. (Both Figure 4.7 and Figure 4.8 indicate that incorporating relocation distance considerations will lead to a decrease in compactness. If compactness is required it is possible to modify the minimum distance relocation model formulation to obtain compact CMAs as follows.[58]

i) Solve the base relocation model (without relocation distances)

ii) Create a modified version of the minimum distance relocation model where

   a. Remove the clustering component from the objective function.

   b. Add a new constraint that fixes the clustering value to be at most the objective function value from the base relocation model

The modified model will incorporate relocation distances while ensuring that compactness does not deteriorate.

4.4.6. Concluding Remarks

This paper presents several linear integer programming formulations that can be used to incorporate relocation distances in designing conservation management areas (CMAs). We apply the models to a real data set pertaining to a military installation where protection of Gopher Tortoise, a keystone species at risk, is of concern. The modeling approach presented here is more general than protection of GTs in a military installation, however, and is applicable to relocating any terrestrial species from their current (but threatened) habitats to protected conservation areas. Though the models are complex, the empirical evidence demonstrates that they are computationally convenient (can be solved within a reasonable computation time, at least for the data set used here). The results of the models are consistent with intuition. It

[58] We thank an anonymous for this suggestion

should be noted that adding the spatial requirements may require the model to select from among less suitable parcels when the best parcels do not meet the specified spatial criteria. This in general leads to the selection of larger CMAs, or poorer compactness of some CMAs. Therefore, there is a trade-off between spatial considerations and reserve size in optimal selection of conservation CMAs.

The grid cells (sites) considered as decision units in this study are rather large (900mx900m). In many practical CMA design problems much smaller areas may have to be considered as decision units, depending on various factors such as data accuracy, site costs, and uniformity of each site in terms of habitat characteristics. This may increase the model size considerably and computational difficulties may arise. For conservation analyses that require higher resolution, it is possible to conduct a multi-step modeling approach, where low resolution data is used to locate the general area and successively higher resolution data is used for the surrounding area in successive model runs. In each successive run the model may be restricted to the area selected in the previous run and the large grid units in that selection can be divided into sufficiently small spatial decision units to identify the specific conservation areas at desired resolution.

According to these relocation model results, it is possible to form up to four centrally placed CMAs within the new military areas that are in close proximity to the original GT habitat areas. The CMAs become smaller and more compact, and comprise higher quality sites as the allowed number of CMAs is increased. However, they may be dispersed throughout the installation area. These results provide general guidelines and will be useful for on the ground decision makers. Perhaps the most important empirical finding of this study is that regardless of the spatial considerations imposed in each case, the GT habitat conservation objective can be served by designating a little amount of land, thus without significant sacrifice in the use of the military area for training purposes.

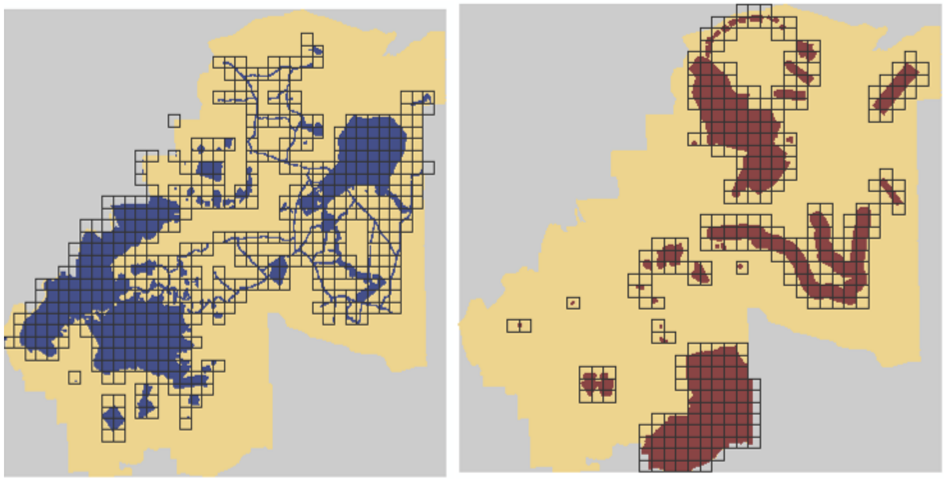
The methods specified can also be expanded to consider species relocation due to climate change. Given probabilistic information about the future suitability of land under various climate change scenarios the model can identify the best reserve areas. The difference from the current application will be that the ecological suitability information will reflect the expected suitability instead of the actual current carrying capacity. The difficulty of doing such an application lies not with the site selection model but rather on being able to generate realistic expected ecological suitability values based on ecological and climate models.

Finally, it should be noted that this paper is more than an empirical analysis of GT conservation in a military area. By successfully incorporating ecological and spatial consideration into linear site selection models, we illustrate that it is possible to generate optimally designed conservation CMA configurations for species relocation using integer programming. With appropriate modifications, the methods introduced here are applicable to many other conservation problems involving endangered and at-risk species and can be extended to include multiple species and multiple land use (See Moilanen et al. 2005 and Dissanayake et al. 2011 for examples of multiple land use reserve design formulations and Polasky et al. 2005 and Polasky et al. 2008 for examples conservation land use within a working landscape). The methods presented in this paper can also be applicable to many other problems of land use/allocation, such as optimal selection of nature CMAs, districting, or optimal urban expansion. For instance, determining optimal locations of open spaces (nature reserves) in and around urban areas has much similarity to the relocation problem addressed here.[59] Therefore, we view the methodological aspects of the paper as equally valuable as its empirical findings for the particular problems we dealt with.

[59] The importance of movement distances may be seen as overemphasized in the GT relocation problem (as relocation is to occur only once, thus the cost involved would be little), but the distances between 'origins' (urban areas) and 'destinations' (open spaces) may be of serious concern in the nature reserve design problem where it is desirable to locate nature reserves as close as possible to urban areas (to serve as open spaces). The excessive cost of numerous repeated trips by numerous people between the urban areas and open spaces over a long time horizon would be substantial even if the total distance is slightly suboptimal. See Ruliffson et al. (2003) and Önal and Yanprechaset. (2007) for a formulation of a site selection problems that incorporate distance to urban areas.

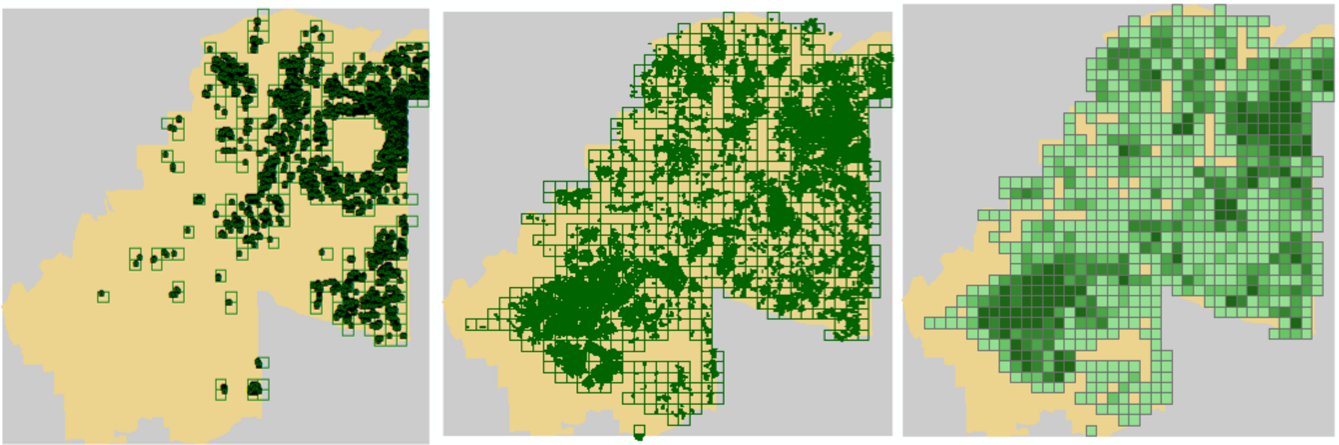
4.4.7. Figures and Tables

Figure 4.4 – a) Locations with current intensive military use; b) Proposed areas for additional intensive military use



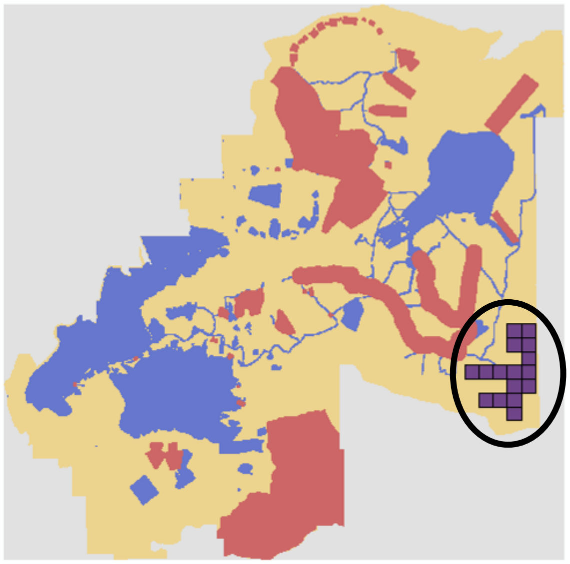
(a) (b)

Figure 4.5 - a) Location of observed GT habitats (based on burrow counts); b) Location of suitable GT habitat areas, c) Quality of suitable habitat areas (darker shade indicates higher quality)

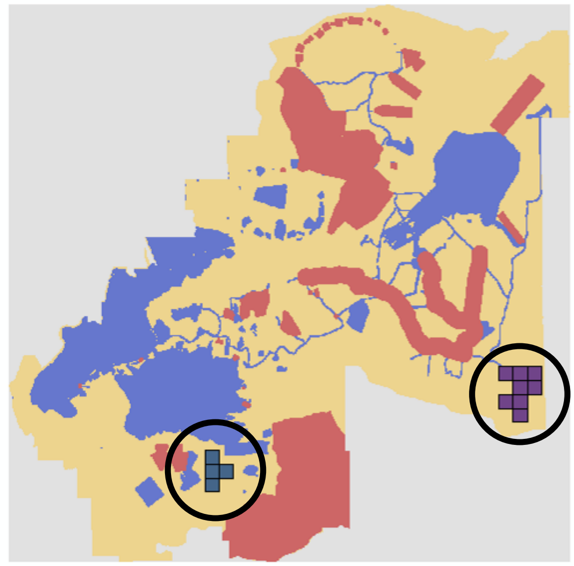


(a) (b) (c)

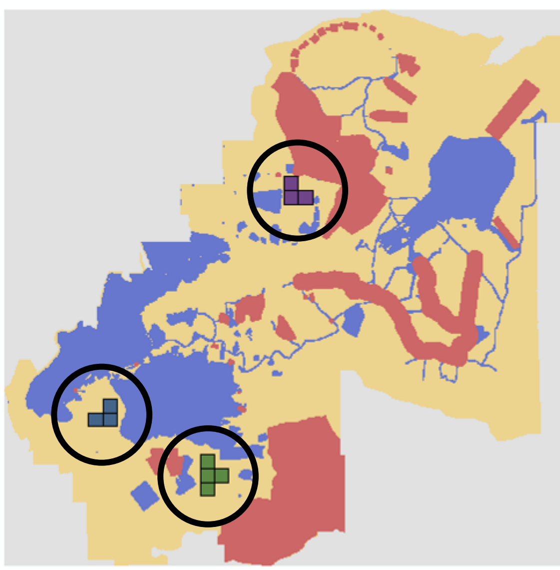
Figure 4.6 – Relocation Model I; solutions for compact reserve configurations



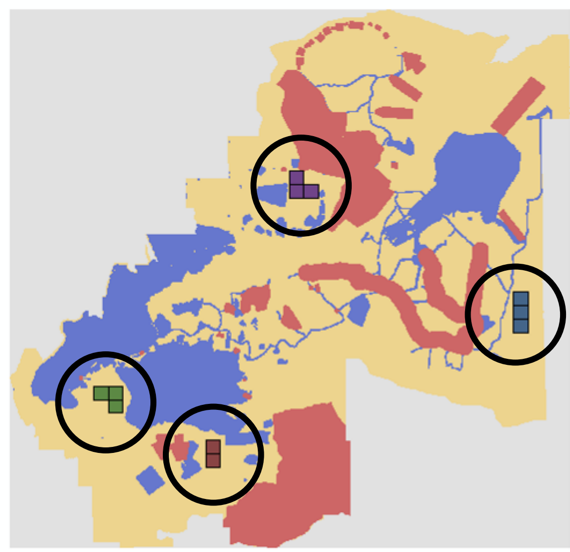
(a)



(b)



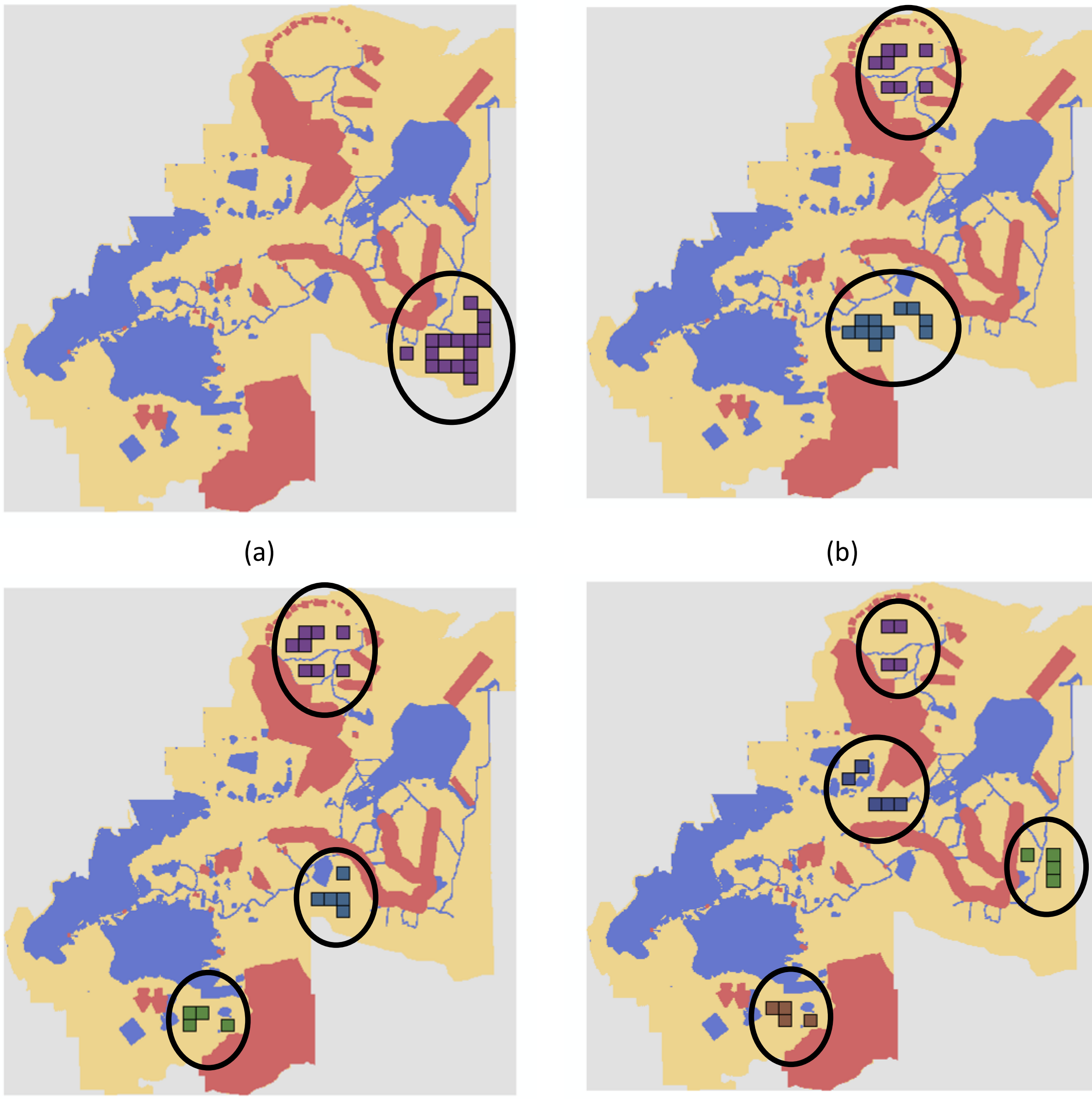
(c)



(d)

(a) one reserve; (b) two reserves; (c) three reserves; (d) four reserves. The lighter shaded areas indicate the current (blue) and proposed (red) military training areas, while the darker shaded areas (shown with the parcels included) indicate the conservation sites chosen by the model. Black circles are used to identify the selected reserves.

Figure 4.7 – Relocation Model II; solutions for compact reserve configurations that minimizes movement distances



(a) (b) (c) (d)

(a) one reserve; (b) two reserves; (c) three reserves; (d) four reserves. The lighter shaded areas indicate the current (blue) and proposed (red) military training areas, while the darker shaded areas (shown with the parcels included) indicate the conservation sites chosen by the model. Black circles are used to identify the selected reserves.

Figure 4.8: Efficiency frontier of the tradeoff between compactness and relocation distance

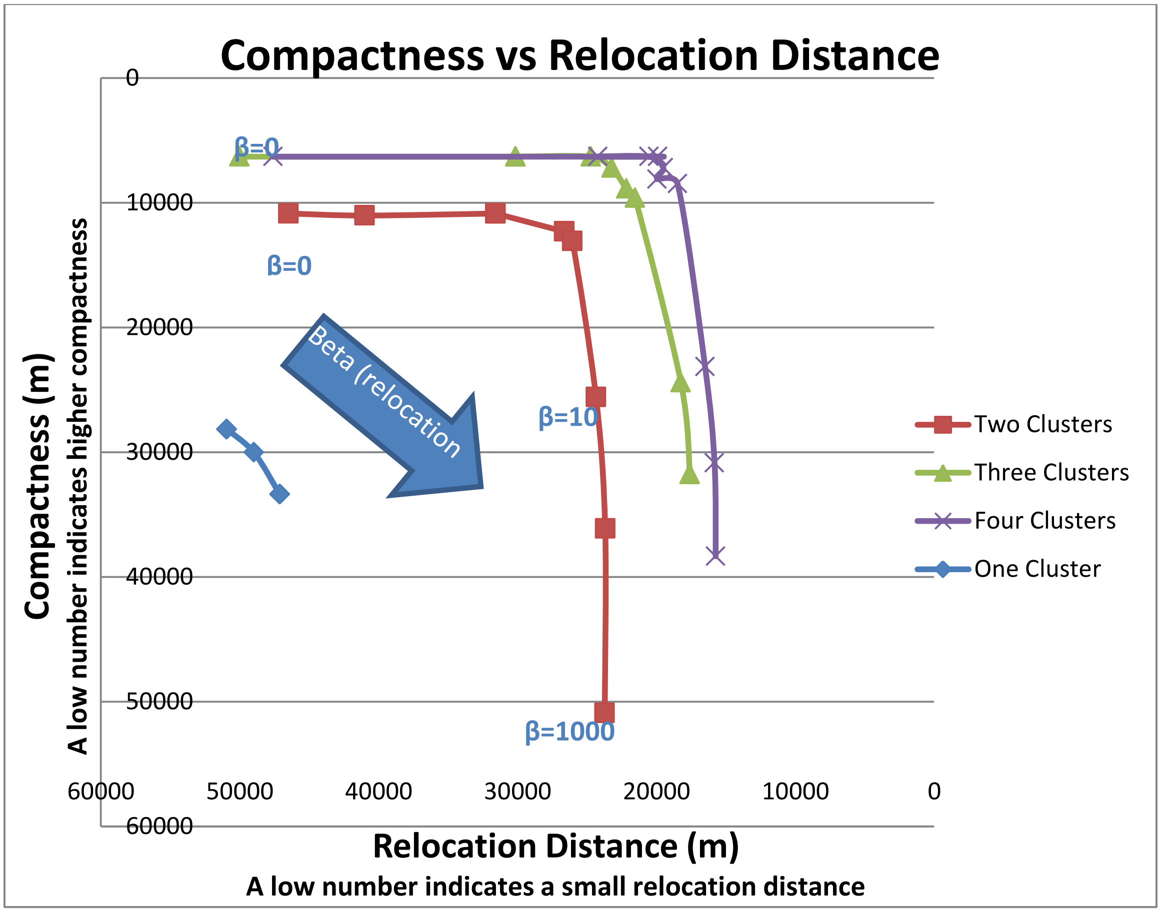


Table 4.1: Analysis of the Sensitivity of Objective Function Weights

Number of clusters	Beta	Total number of sites	Compactness (total cluster distance (m))	Total relocation distance (m)
1	0	16	28162.14	50938.46
1	0.001	16	28162.14	50938.46
1	0.01	16	28162.14	50938.46
1	0.1	16	28162.14	50938.46
1	0.5	16	28162.14	50938.46
1	1	16	30017.78	48980.66
1	2	16	33382.85	47118.88
1	10	16	33382.85	47118.88
1	100	16	33382.85	47118.88
1	1000	16	33382.85	47118.88
2	0	12	10858.05	46505.47
2	0.001	12	11018.38	41010.52
2	0.01	12	10858.05	31585.90
2	0.1	12	10858.05	31585.90
2	0.5	11	12303.04	26637.97
2	1	11	12303.04	26637.97
2	2	11	13048.63	26055.07
2	10	16	25567.93	24354.05
2	100	19	36111.23	23692.47
2	1000	27	50905.32	23722.99
3	0	10	6300.00	50013.30
3	0.001	10	6300.00	30144.56
3	0.01	10	6300.00	30157.51
3	0.1	10	6300.00	24730.51
3	0.5	11	7200.00	23233.27
3	1	12	8845.58	22170.97
3	2	12	9591.17	21544.67
3	10	16	24401.81	18240.86
3	100	17	31765.65	17595.39
3	1000	17	31765.65	17595.39
4	0	11	6300.00	47607.24
4	0.001	11	6300.00	19911.26
4	0.01	11	6300.00	24225.34
4	0.1	11	6300.00	20519.44
4	0.5	12	7200.00	19500.50
4	1	13	8100.00	19947.83
4	2	13	8472.79	18480.07
4	10	17	23146.81	16497.95
4	100	18	30851.55	15816.94
4	1000	21	38343.65	15737.16

4.5. Optimal Selection of Conservation Lands for Dependent Species: The Case of Gopher Tortoise and Gopher Frog at Ft. Stewart, GA.

This chapter demonstrates the use of linear integer programming formulations to identify the sites for forming clustered biodiversity management areas within the boundaries of a military installation. We present a basic clustered site selection model and extend the model to include a secondary species. We apply the models to a dataset related to Gopher Tortoise (GT), a key stone species currently considered 'at risk', and Gopher Frog, a species dependent on GTs and access to ponds, at Ft. Stewart, Georgia.

4.5.1. Problem Statement

Ft. Stewart, GA, is an example of a military base engaged in biological conservation. Ft. Stewart currently has an extensive population of Gopher Tortoise (*Gopherus polyphemus*), referred to as GT. The GT is a keystone species and is listed as a species at risk (SAR). Ft. Stewart also has a population of another SAR species Gopher Frog (*Rana capito*), referred to as GF, that depends partly on GT burrows for survival. In an effort to best manage the GT and GF populations, Ft. Stewart is looking into the optimal selection of habitat areas that can be made available for the protection of these two species (among others, such as Indigo Snake and Striped Newt). The study aims to develop optimum land use strategies for the installation by incorporating various ecologically important considerations when determining the best possible management areas without hampering the military training activities.

The mathematical programming models developed here identify the conservation management areas (CMA) to achieve/maintain desired levels of GT and GF populations while giving special emphasis to the location and size of the CMAs. Since GT is a ground-bound species, the selected areas should be as 'compact' as possible, and preferably 'contiguous', in order to allow movement of individuals in the selected areas and facilitate interaction within and among multiple populations in those areas. A compact CMA would also be easier to fence, if needed. Furthermore, since GT is a keystone species and the GF relies on GT burrows to survive, incorporating the GF management areas into the model would further increase the efficiency of CMA selection because joint management of two species is always more efficient than independent management of individual species. Since the GF depends on access to water for a portion of their life cycle, the distances of GF sites to both ponds and nearest GT habitat sites need to be considered when determining the best GT sites.

In light of the above, specifying the most suitable CMAs for GTs must involve various important ecological and spatial considerations including the following: i) each designated CMA must have a minimum size, either specified in terms of the land area or in terms of the GT population in that CMA; ii) each CMA should preferably have a compact (circular or square-like) shape; iii) the presence of GF should be considered for joint management efficiency, iv) the GF management areas must be close to both GT sites and existing ponds in the installation area; and most importantly v) land use for conservation must be compatible with the existing military land use and training activities.

4.5.2. Methods

We denote the set of all sites by *L* and denote individual sites by $k, l \in L$. Site selection and assignment to a CMA is represented by a binary variable X_{lk}, where X_{lk} =1 if site *k* is selected and belongs to the CMA centered at site *l* and X_{lk} =0 otherwise. Note that by construct X_{ll} =1 for all central sites *l*, i.e. the central site of each CMA must belong to that CMA. We also note that sites in the most heavily used military training areas (existing or potential) are not considered for inclusion in any CMA, therefore we set X_{lk} =0 if site *k* is part of a training area. The symbol d_{lk} denotes the distance between site *l* and site *k*, and e_k denotes the existing population of GT in site *k*. The number of CMAs (clusters) to configure is denoted by *n*; which is specified exogenously, but varied when designing alternative optimal configurations. Each CMA is required to sustain a minimum GT population, denoted by *p*. Finally, the total GT population in all the selected areas is represented by *tp*.

4.5.2.1. Base Model

We first address the problem of constructing *n* compact CMAs for GTs, each covering a minimum sustainable GT population and collectively covering a desired GT population. Here we define compactness of a CMA as the overall 'closeness' of all sites in it. We measure the latter by the sum of distances from all sites in a cluster to the central site of that cluster, which must be minimized to the extent possible[60]. An algebraic model that serves this purpose, which will be referred to as the '*Base Model*' from here on, is given below.

$$(2.1) \quad \text{Minimize} \ \sum_{l} \sum_{k} X_{lk} * d_{lk}$$

such that:

$$(2.2) \quad \sum_{l} X_{ll} = n$$

$$(2.3) \quad \sum_{l} X_{lk} \leq 1 \ \text{ for all } k$$

$$(2.4) \quad \sum_{k} X_{lk} * e_k \geq p \ \text{ for all } l$$

$$(2.5) \quad \sum_{l} \sum_{k} X_{lk} * e_k \geq tp$$

$$(2.6) \quad X_{lk} \leq X_{ll} \ \text{ for all } l,k$$

$$(2.7) \quad X_{lk} = 0,1 \ \text{ for all } l,k$$

The objective function involves the distances from individual sites in each CMA to the 'center' of that CMA, which in turn is summed over all CMAs. Minimizing this sum of distances achieves a clustered CMA. Constraint (2.2) ensures that *n* CMAs are created. Constraint (2.3) states that each site can belong to at most one CMA centered at some site *l*. Constraint (2.4) requires that

[60] Compactness is not a well-defined concept. Note that the absolute value of the compactness measure defined here may not mean much just by itself, rather it has to be considered together with the size of the reserve (number of sites involved). This is because a reserve with only a few distant sites may have a smaller total distance value than a reserve with too many tightly packed sites, whereas in practice the latter should be considered more compact. Although not being fully satisfactory, this definition well serves the specific purposes of the present study. Minimizing the total distance typically results in a circular and connected reserve configuration.

each CMA supports a population that exceeds the minimum sustainable size[61], while constraint (2.5) ensures that all CMAs collectively support a desired total population. Finally, constraint (2.6) implies that if site *k* is selected and assigned to the central site *l*, i.e., X_{lk} =1, then a CMA centered at site *l* must be formed, i.e. X_{ll} must be 1, otherwise we have X_{lk} =0.

The Base Model identifies the most suitable clusters to be considered as CMAs for GTs. However, it does not incorporate GF considerations. We next present a modification to the model that determines GT and GF management areas simultaneously.

4.5.2.2. Simultaneous Selection of CMAs for GT and GF

The best CMAs for both GT and GF must have the following properties: i) the GT CMAs must be as compact as possible; ii) each CMA must be large enough to include a sustainable GT population; and iii) individual CMAs must contain a minimum number of GF sites that are within 2 km of an existing pond. The first two criteria are already included in the Base Model formulation. The last criterion is necessary since the GF life cycle requires access to a reliable water source and the maximum distance from a water source is known as 2 km.

In addition to the notation used earlier we define a new binary variable Y_k for site *k*, where Y_k = 1 if site *k* is selected as a designated GF habitat area and Y_k = 0 otherwise[62]. We also define the following new symbols: f denotes the desired minimum number sites assigned as GF parcels; dp_k denotes the distance between site *k* and the nearest pond, and $\bar{d}$ denotes the maximum allowed distance between a designated GF site and the nearest pond. Adding the two constraints below to the Base Model incorporates the GF management area requirements:

[61] This constraint can also be expressed in terms of a minimum number of sites in each CMA if the effectiveness of conservation effort is related to the size of the CMAs.
[62] As formulated we require that only sites selected as GT sites can be considered as GF sites

$$(2.7) \qquad Y_k \le \sum_{l} X_{lk} \quad \text{for all } k$$

$$(2.8) \qquad \sum_{k:dp_k \le \bar{d}} Y_k \ge f$$

$$(2.9) \qquad Y_k = 0,1 \quad \text{for all } k$$

Constraint (2.7) ensures that only sites selected as GT sites can be considered as a GF site. In other words, if site k is designated as a GF site (i.e. $Y_k = 1$) then it must be assigned to some GT CMA centered at site l ($X_{lk} = 1$). Constraint (2.8) ensures that the model selects at least f GF sites. Note that a GF site can be considered as a designated site only if its distance from a pond is at most $\bar{d}$, as implied by the condition underlying the summation in (2.8).

4.5.3. Data

The data on current military training areas and the location of ponds were obtained as raster files from Ft. Stewart. The habitat areas suitable for GT were obtained as raster files from the national biological information infrastructure (Elliott et al.2003). The above raster files were converted to ESRI shape files using ArcGIS 9.2. The current military training areas are shown in Figure 4.10.a, the GT suitability is depicted in Figure 4.10.b, and the locations of the ponds are shown in Figure 4.10.c. A 55x30 grid file, where each grid cell is a 1000m x 1000m square, was created using GeoDa and the grid shape file was spatially joined with the above shape files using spatial join tool in ArcGIS. The spatial join gives the grid file the attributes of the shape file. To ensure that each grid cell represents a density of the original data, the "sum" option was used when joining the habitat suitability data. The grid cell values for Figure 4.10.b are given as the sum of suitable points (the GT suitability raster map[63] was converted to point shape file)

[63] GT Suitability values were calculated by Dr. James D. Westervelt and Dr. Tracey Tuberville.

within the grid cell. The suitability index ranges from 0 to 600[64].

4.5.4. Results and Discussion

The models described by (2.1)-(2.6) and (2.1)-(2.9) were solved using GAMS/CPLEX version 21.6 on a PC with an Intel Core 2 Duo processor and 2 GB of RAM running Windows XP. It is assumed that the final total GT population in all CMAs must be at least 5000. In theory, the GT populations can be moved to a single large CMA or multiple smaller CMAs (all located outside the military training areas). The model is solved with various specifications for the number of CMAs. There are two reasons for specifying more than one CMA. First, we may want to separate the overall GT population into smaller populations, each being located in a different part of the installation area, to safeguard them against a potential total destruction that may occur in the managed areas (such as spread of a potential disease in one area to the other areas). Second, setting aside one large conservation area reduces the flexibility for the military when further expansion of training areas is needed in future. These problems can be alleviated or reduced by designing multiple and relatively small conservation areas.

In all of the runs described below the minimum population for each CMA was specified as 1000. The Base Model was solved with one, two, three and four CMAs. The joint management model (2.1)-(2.9) was first solved for a minimum of 10 GF parcels and then for 20 GF parcels[65]. A wide range of potential parameter values were tested after discussions with the Base Land Managers. We only present these results here to highlight the models ability to i)

[64] The carrying capacity values in the suitability map are GT/ha. The number of tortoise in each grid cell = (suitability value of grid cell/121)*100. A one-hectare land parcel can support between 2 to 5 GT's. This is equivalent to supporting between 200–500 GTs per site at the 1000m x 1000m resolution.

[65] The only GF criteria we required are that a GF site has to be a GT site and also be within 2 km of a pond. These criteria can be refined based on the available data. For example instead of considering all ponds, only ponds that are larger than a certain size or have water during the GF breeding season.

optimally select the CMAs, ii) illustrate the workings of the models, and iii) demonstrate the trade-offs between incorporating different spatial criteria in site selection.

4.5.4.1. Base Model Results

First we show the results for a basic set covering problem (1.1) – (1.3) from the introduction section. The result for tp = 5000 GTs is given in Figure 4.9.a. Four of the six management areas (including 12 sites in all) are comprised by single parcels and they are scattered across the installation. The result for 5000 GTs and 20 GF sites is given in Figure 4.9.b, which again shows that the selected sites are scattered across the installation. Due to the lack spatial coherence neither of the two selections would be considered as good solutions as it would be costly and ecologically impractical to manage too many small and spatially dispersed sites.

The Base Model results are shown in Figure 4.11 for one, two three, and four CMAs. Comparing the results in Figure 4.11 with the suitability map given in Figure 4.10.c illustrates that the Base Model simply selects from amongst the most densely packed and best available sites to form contiguous and compact CMAs. The optimal solution with one large conservation area (Figure 4.11.a) shows that this area would be located at the southwest corner of the installation. The CMA is contiguous but the compactness of the CMA is poor and the selected sites are meandering in shape. Also, the solution has 16 sites as opposed to the 12 sites in the basic set covering problem (see Figure 4.9.a). The lack of compactness and the increase in the number of selected sites are both driven primarily by the fact that the model is forced to choose one cluster of habitat sites that meet the population criteria and the only available large quantity of good quality sites are in that part of the installation. The good quality sites in other parts of the installation are not in the solution due to two reasons: i) those sites are under military use, or ii) those sites are located far apart from each other.

For the two-CMA case the model chooses two clusters with seven and eight sites, respectively (Figure 4.11.b) for a total of 15 sites. Although the two clusters are again selected in the southwest corner of the installation, allowing for two clusters enables the model to achieve the population goal with one less site than the previous (one-cluster) case. The three-CMA case selects a total of 14 sites (Figure 4.11.c), with two clusters in the southwest part of the installation and one cluster in the north-central part of the installation. inally, the four CMA case selects 13 sites from three separate areas as shown in Figure 4.13.d. This clearly demonstrates that as more CMAs are considered the model is able to choose fewer and better sites in different parts of the installation decreasing the total area needed for the same level of conservation. Unlike the one big CMA scenario, the two, three and four-CMA configurations are comprised of compact clusters of sites as opposed to the meandering configuration in Figure 4.11.a. Based on these results, we may conclude that if the size of the total area of all CMAs is a concern, forming four CMAs, two located in the southwest, one located in the west-central area and one located in the north-central areas, is the best strategy as it selects 13 sites only. It is noteworthy to state that this alternative includes just one more site than the scattered configuration given in the set covering solution (Figure 4.9.a).

4.5.4.2. Joint management Results

The results of the joint management model (2.1)-(2.9) are shown in Figures 4 – 7 for one, two, three and four CMAs respectively. In each of the Figures 4 – 7, Figure x.b displays the results for at least 10 GF sites (*f*=10) and Figure x.c displays the results for at least 20 GF sites (*f*=20). The optimal solution with one large conservation area and 10 GF sites (Figure 4.12.b) shows that this area would again be located at the southeast corner of the installation and is identical to the solution without GF considerations. This is because as depicted in Figure 4.12.d, there are 10 sites in that area that is within 2 km distance from a pond in that solution. When the number of GF sites is increased to 20 sites the selected sites are still in the southwest corner of the installation, but the locations change since the model now has to add more sites that are located within 2 km from a pond.

The results for two CMAs are shown in Figure 4.13. For 10 GF sites the optimal configuration is similar to the base model solution. However, when 20 GF sites are required the results change dramatically, the model selects one compact CMA with 9 sites and another one with 11 sites that are located away from each other and close to the locations of the ponds. The results for three CMA's are shown in Figure 4.14. In the base model solution one CMA was located in the north-central region away from ponds. The case with 10 GF sites (Figure 4.14.b) now moves that CMA located away from the ponds to a region with nearby ponds without increasing the total number of selected sites. The case with 20 GF sites (Figure 4.14.c) again selects more sites and has three CMAs that are located in different regions of the base. The solution including four CMAs (Figure 4.15) shows that it is possible to meet the 5000 GT population and the 10 GF site goals with only 13 sites, just one more site than the set covering solution and same as the GT-only solution. When requiring 20 GF sites the optimal selection includes more sites that are located in the west side of the installation and part of the nicely grouped compact GT clusters. Clearly this is a much more preferred configuration, as opposed to the spatially unrestricted (and thus scattered) configuration shown in Figure 4.9.b. In general allowing for four CMA's results in more compact CMAs since the model is able to place the smaller CMAs in the most suitable areas, yet the individual CMAs are large enough to support a minimum viable population of GTs assumed in the analysis.

4.5.5. Conclusions

This chapter presents an application of linear integer programming to determine compact and ecologically valuable conservation management areas (CMA)s in a military installation. Two models are developed and applied to the conservation efforts currently undertaken at the Ft. Stewart installation involving the Gopher Tortoise (GT), a key stone species, and the Gopher Frog (GF), both identified as species at risk. The GF depends on GTs presence in protected areas and also requires proximity to ponds for breeding. The results of the models are consistent with intuition and reflected the desired outcomes;

- The models selected compact GT clusters
- Considering multiple CMAs reduces the total amount of managed areas by selecting fewer and better sites
- Incorporating GF requirements into the GT analysis does not change the results for a small number of GF sites but the results change considerably for a large number of GF sites.

We note that both the single and joint species conservation management models are solvable in a short computation time, which suggests that the formulations presented here can be applied to much larger data sets. In all cases, the optimum solutions were obtained only in a few minutes of processing time. It should also be noted that adding extra requirements to the model, such as the additional GF conservation requirements, may force the model to select from among less suitable parcels when the best parcels do not meet the specified criteria. This can lead to the selection of larger CMAs, or poorer compactness of some CMAs. Therefore, there is a trade-off between incorporating additional requirements and the economic efficiency in optimal selection of conservation CMAs.

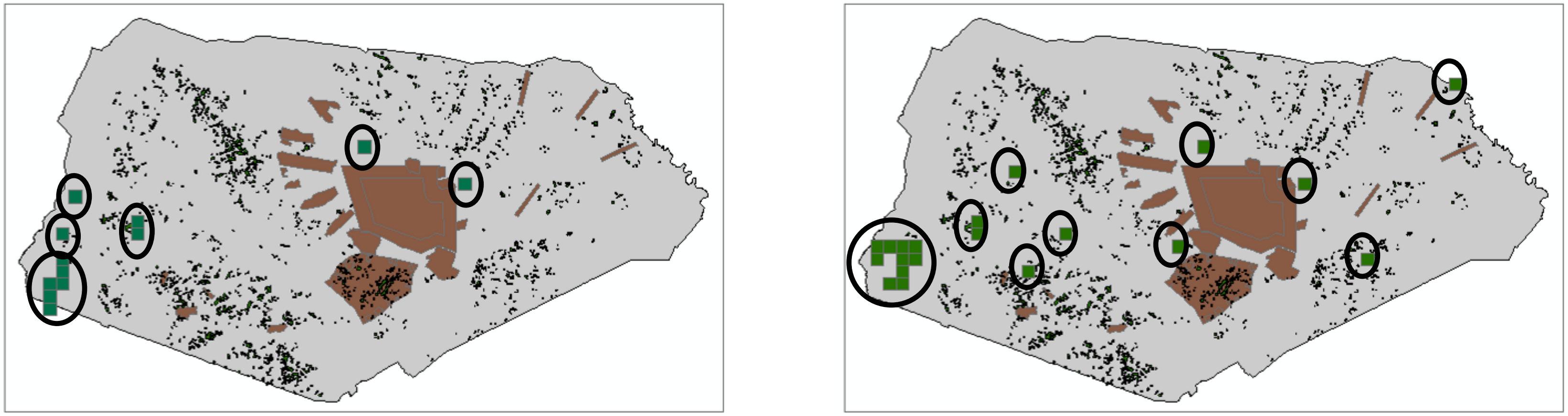
The grid cells (sites) considered as decision units in this study are rather large (1000mx1000m). In many practical CMA design problems much smaller areas may have to be considered as decision units, depending on various factors such as data accuracy, site costs, and uniformity of individual sites in terms of their habitat characteristics. This may increase the model size considerably and computational difficulties may arise. For conservation analyses that require higher resolution, it is possible to conduct a multi-step modeling approach if necessary, where low resolution data can be used first to locate the general area and successively higher resolution data can be used for the surrounding areas in successive model runs. In each successive run the model may be restricted to the area selected in the previous run and the large grid units in that selection can be divided into sufficiently small spatial decision units to identify the specific conservation areas at desired resolution.

According to the results presented here, it is possible to identify the optimum selection of compact sites that form up to four centrally placed CMAs within the boundaries of the particular military installation. The CMAs become smaller and more compact, and comprise higher quality sites as the allowed number of CMAs is increased. However, they may be dispersed throughout the installation area. When GF considerations are included, the model identifies CMA's that simultaneously serve as good GT habitats and also GF habitats indicating that ecological considerations for multiple species can be incorporated in a unified framework.

Perhaps the most important empirical finding of this study is that the GT habitat conservation objective can be served by designating only a small amount of land, thus without significant sacrifice in the use of the military area for training purposes. Finally, it should be noted that this chapter is more than an empirical analysis of GT conservation in a military area. By successfully demonstrating how ecological and spatial consideration can be incorporated into linear site selection models, we illustrate that it is possible to generate optimally designed CMA configurations for multiple species using integer programming. With appropriate modifications the methods introduced here can be applicable to many other conservation problems involving endangered and at-risk species and can be extended to include multiple land use.

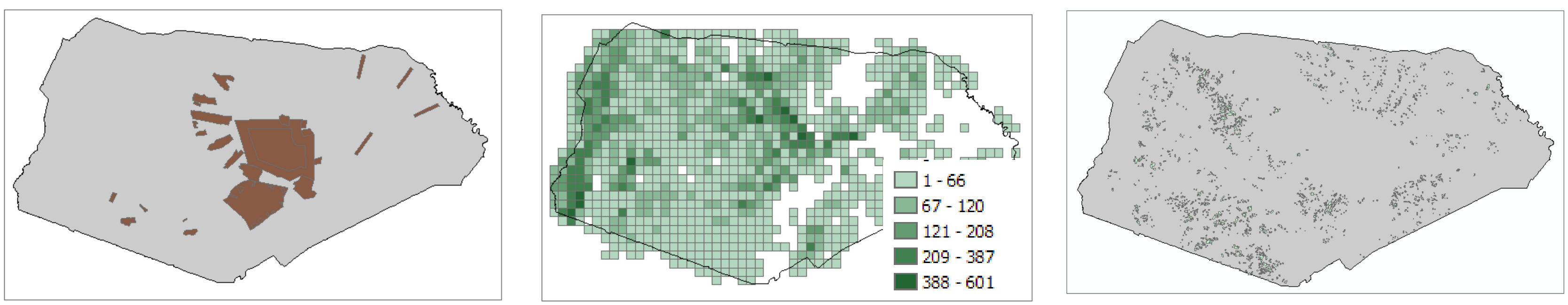
4.5.6. Figures

Figure 4.9: Results for basic set covering problem with total carrying capacity index of 5000



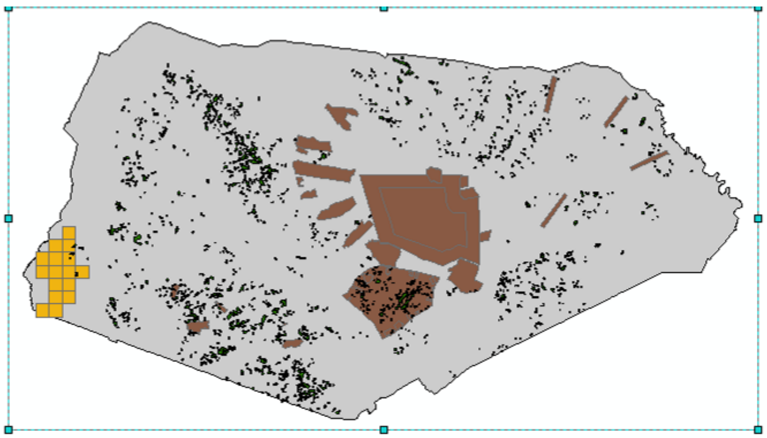
(a) No Gopher Frog (b) 20 Parcels of Gopher Frog

Figure 4.10: Summary of Data

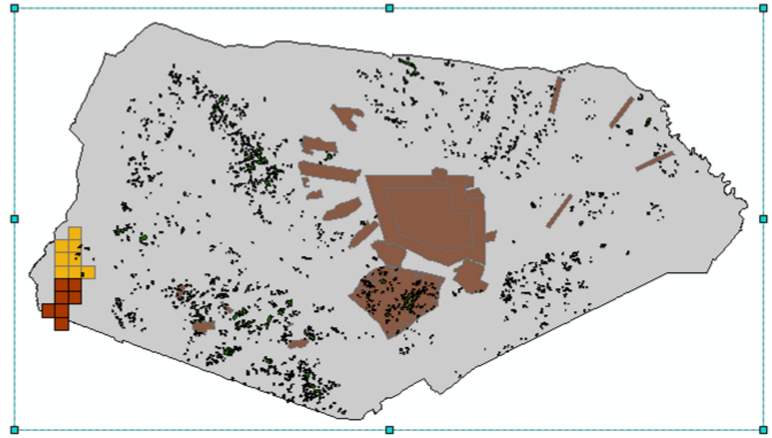


Ranges Suitability Index for GT Location of Ponds

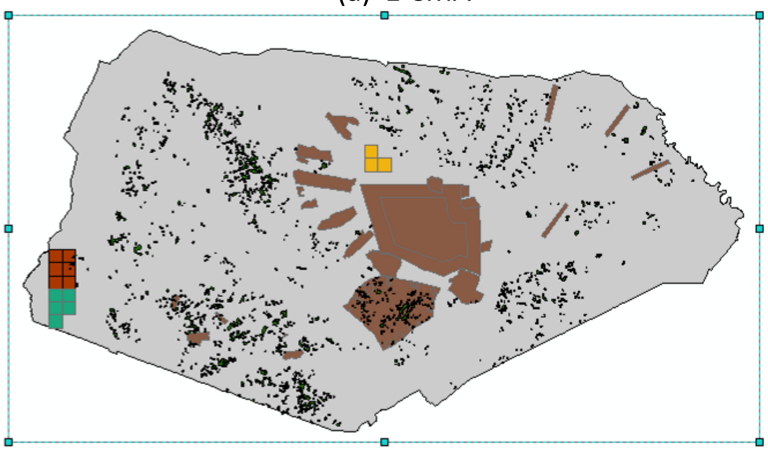
Figure 4.11: Results for total carrying capacity index of 5000



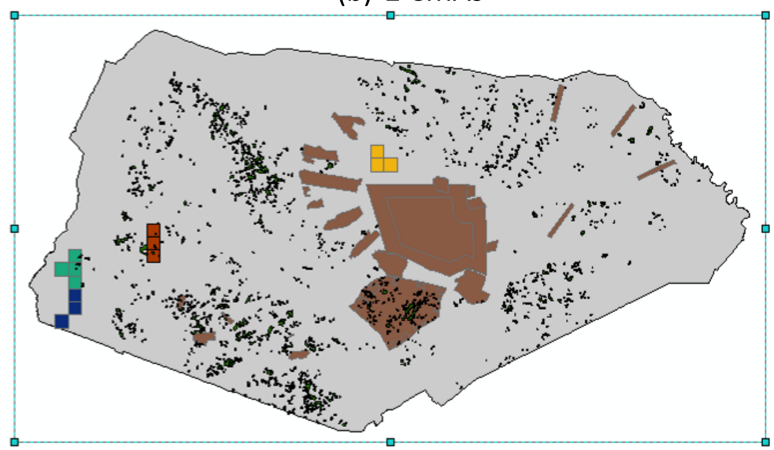
(a) 1 CMA



(b) 2 CMAs

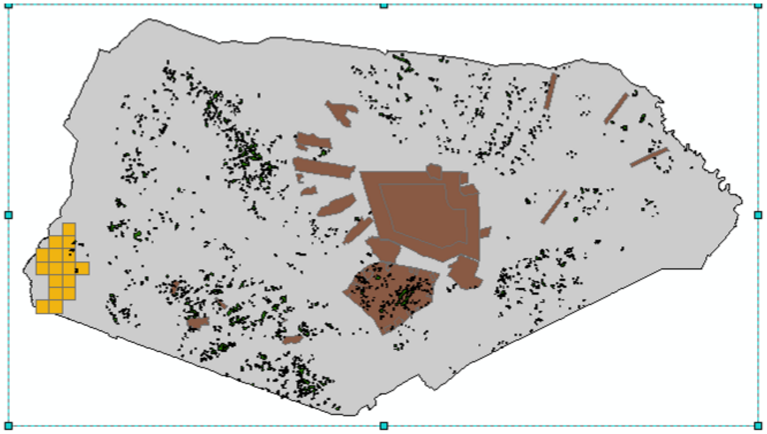


(c) 3 CMAs

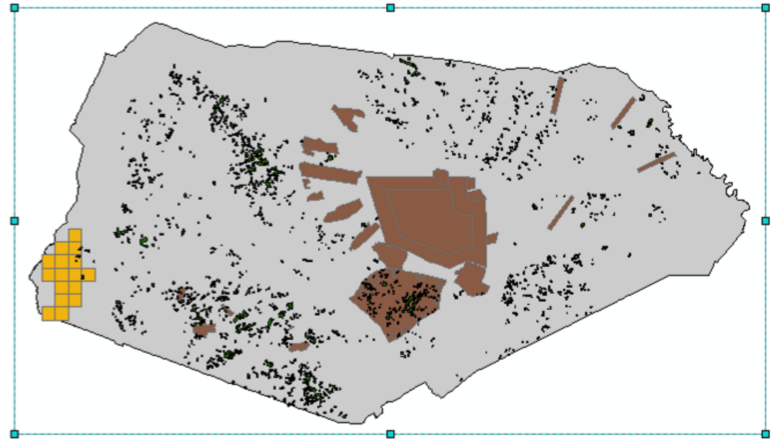


(d) 4 CMAs

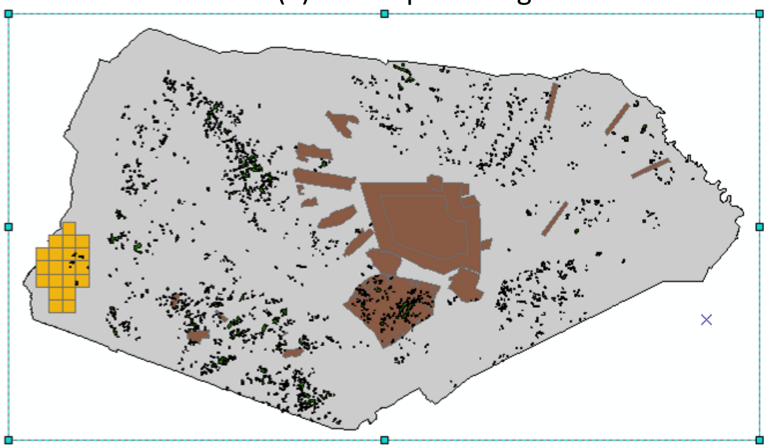
Figure 4.12: Results for 1 cluster of GT with total carrying capacity index of 5000



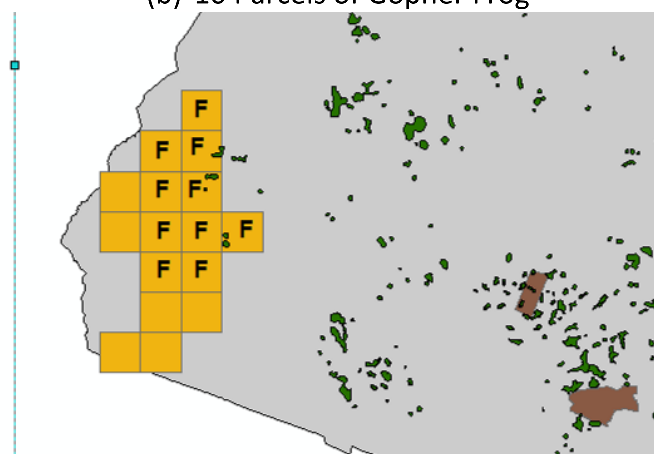
(a) No Gopher Frog



(b) 10 Parcels of Gopher Frog

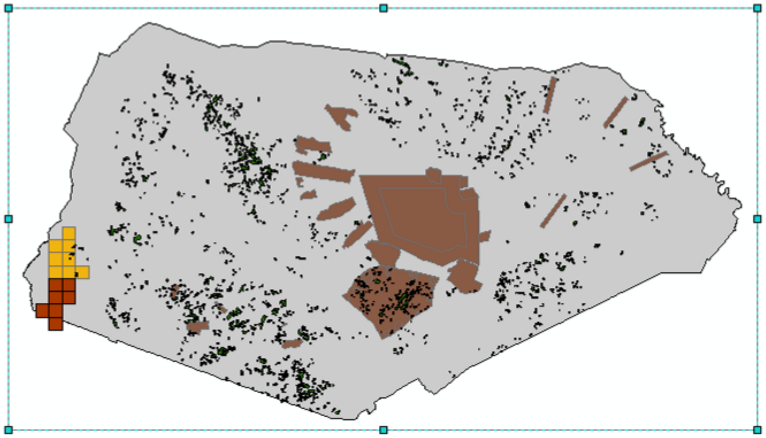


(c) 20 Parcels of Gopher Frog

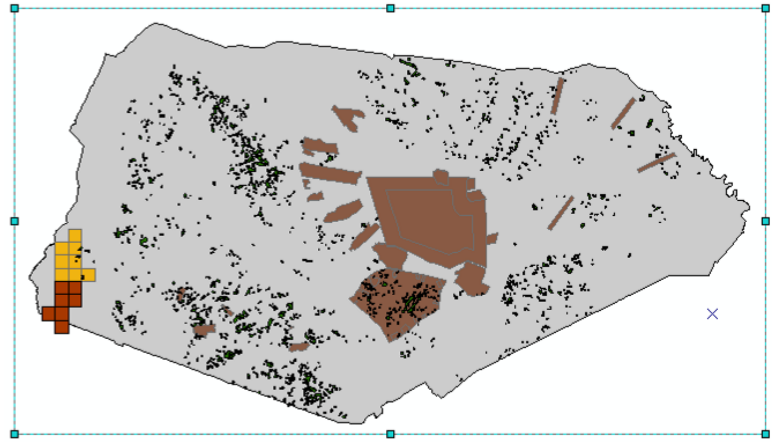


(d) 10 Parcels of Gopher Frog (identified with F)

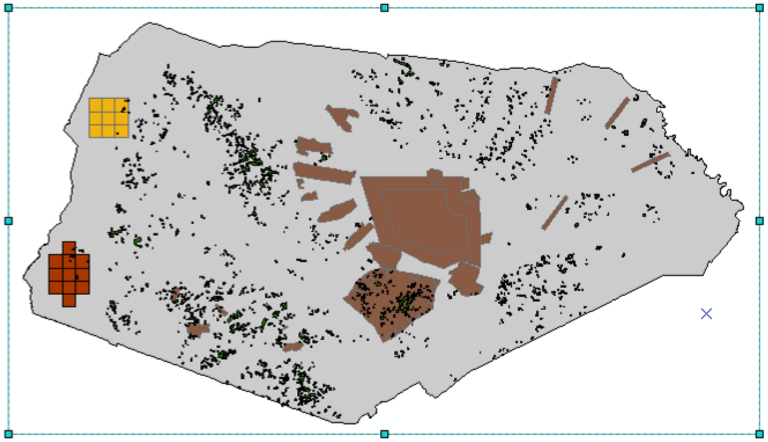
Figure 4.13: Results for 2 clusters of GT with total carrying capacity index of 5000



(a) No Gopher Frog

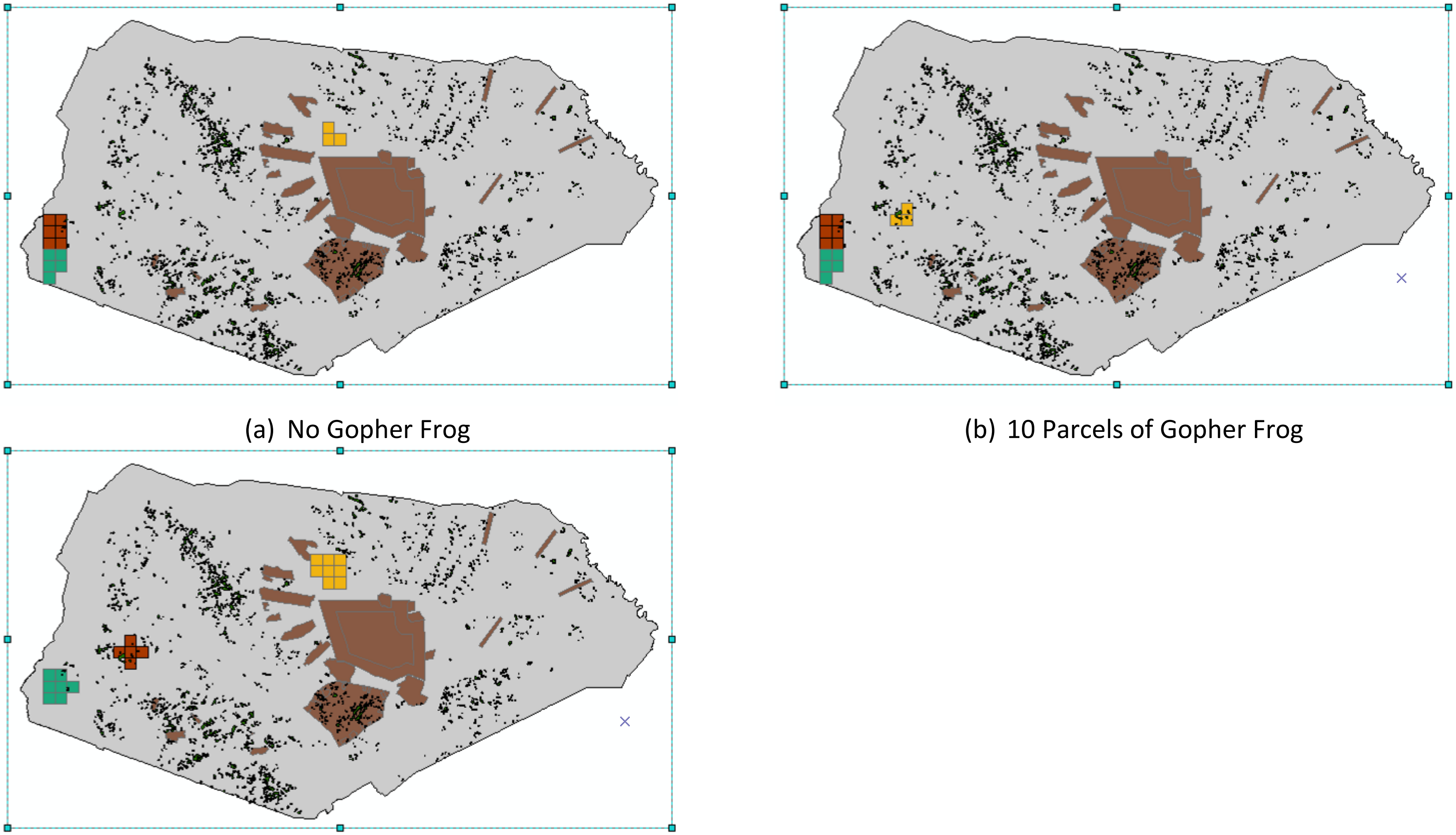


(b) 10 Parcels of Gopher Frog



(c) 20 Parcels of Gopher Frog

Figure 4.14: Results for 3 clusters of GT with total carrying capacity index of 5000

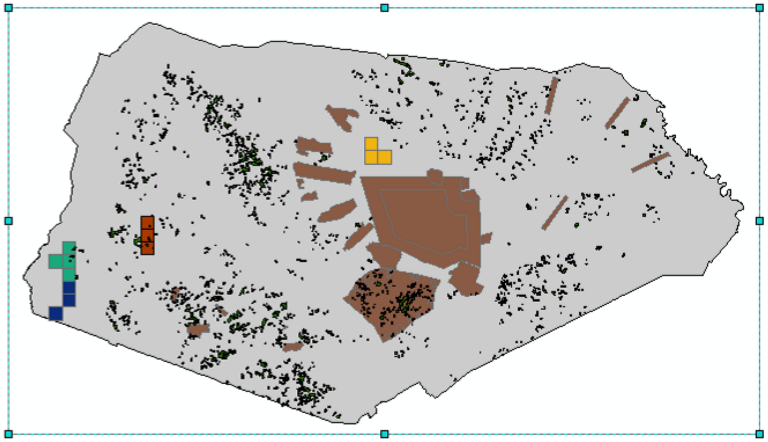


(a) No Gopher Frog

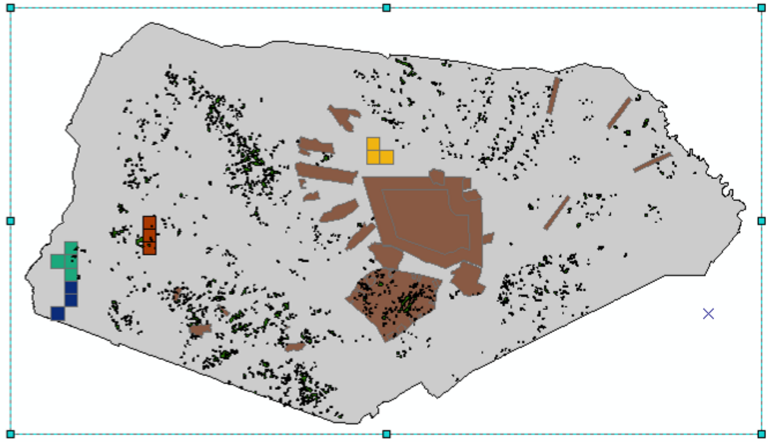
(b) 10 Parcels of Gopher Frog

(c) 20 Parcels of Gopher Frog

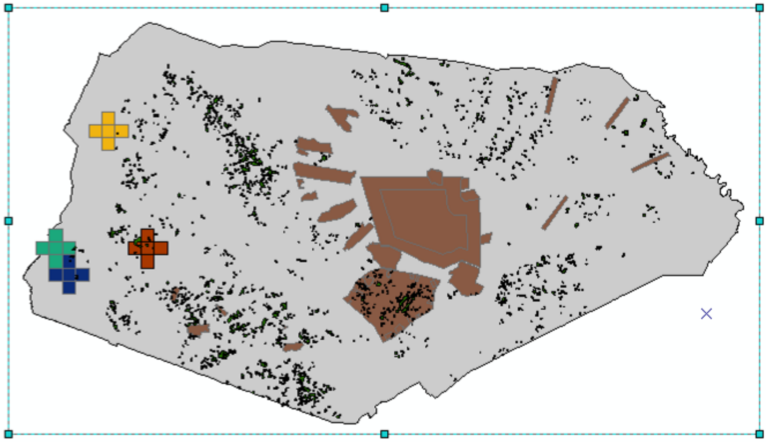
Figure 4.15: Results for 4 clusters of GT with total carrying capacity index of 5000



(a) No Gopher Frog



(b) 10 Parcels of Gopher Frog



(c) 20 Parcels of Gopher Frog

4.6. Optimum Selection of Land for Conservation and Military Use

Military installations are required to protect remnants of suitable habitat areas for rare, threatened, or endangered species in the U.S. while simultaneously addressing land demands to support growing needs for new and conventional training requirements. This leads to an increased pressure to manage federal lands in increasingly optimal ways that balance competing objectives and land uses. Mathematical programming methods, in particular linear integer programming, have been used widely in the biological conservation and reserve design literature. Most of the recent works have focused on one specific land use, namely species conservation. In many cases, however, it is important to simultaneously consider multiple land use within a landscape. We introduce a multiple land use allocation model that includes spatial and ecological criteria and highlight two extensions: a multiple land use meta-clustering model and a multiple land use proximity-to-roads model. A large-scale real data set for the area surrounding Ft. Benning (GA) is used to optimally select reserve conservation areas and military areas. We believe this approach will contribute to the ability of land managers at installations to extract more overall utility from military installation training and testing areas.

4.6.1. The Problem Statement

Most of the recent literature on reserve site design focused on one specific land use, namely species conservation. Exceptions are Lichtenstein and Montgomery (2003), Moilanen et al. (2005), Polasky et al. (2005) and Polasky et al .(2008). Lichtenstein and Montgomery (2003) study the tradeoff between conservation and forestry and Moilanen et al. (2005) present efficient quantitative methods for identifying conservation core areas. Polasky et al. (2005) and Polasky et al. (2008) analyze the conservation outcomes in a working landscape using a combined biological and economic model. They identify the tradeoff between conservation outcomes and economic returns. The above papers focus on the economic returns from the non-conservation areas, but they do not explicitly model the spatial configuration of the non-conservation areas. In many cases, however, not only the conservation areas but the spatial configuration of the remaining areas may also be important. In the problem addressed here this issue is particularly important since the primary objective of the military land use management is efficient functioning of the military training areas that is affected significantly by spatial coherence of those areas, such as the size of the training areas, distances between military sites that are used for joint training activities, accessibility (proximity to roads, contiguity), etc. This paper contributes to the reserve design literature by introducing alternative mathematical programming models to incorporate certain spatial considerations that are important in designing efficient biological conservation and military training areas simultaneously.

The methods presented in this paper are not specific to the problem at hand. Rather, they are general and may have applications in various land allocation situations, such as residential vs. open space or urban vs. industrial uses of lands, etc. In this particular study we focus on the Ft. Benning (GA) military installation where land is to be allocated optimally between military and conservation uses. Specifically, we determine the optimal locations and sizes of conservation areas for Gopher Tortoise (GT), a species listed as a “species at risk”, and military areas for armor training maneuvers.

Ft. Benning is currently an infantry training installation that is expanding to include armor training. The introduction of the armor training will require additional land to be used for training and will require the relocation of GT from within the installation. In this paper, we focus on GT only, but with appropriate modifications, the approaches presented here can be extended to simultaneous consideration of multiple species[66]. Given the presence of GT within the base, land managers at Ft. Benning identify “reserves” for GT within the boundaries of the installation, each exceeding a minimum size (in order to support a minimum viable GT population) while collectively exceeding a specified area size (to support the targeted GT population). In this paper the term “reserve” is used to refer to a conservation management area, a designated tract of land on which military activities are normally less intense and the land is better suited for use as GT habitat. All such areas will still be available for appropriate military training use; however these areas will be selected so as to be among the least disturbed areas. The protection of certain species in the reserve and considerations for their management are always subject to mission requirements and Congressional authority. Since GT is a ground-bound species, the selected areas should be as ‘compact’ as possible, preferably ‘contiguous’, in order to allow movement of GT in the protected areas and facilitate interaction within and between GT populations in those areas. A compact reserve would also be easier to

[66] Ft. Benning also manages habitat areas for ‘Red Cockaded Woodpecker’, another species at risk.

fence, if needed. Furthermore, in case the clusters are separated it would be desirable to have them in close proximity to each other. Similarly, military requires multiple training areas each with a given size and together exceeding a specified total military area. In addition to size restrictions, distances between military sites that are used for joint training activities and accessibility (proximity to roads) are also important considerations when selecting the best sites for military training purposes. We incorporate all the above requirements simultaneously in our analysis and develop alternative mathematical models for the purpose. These models are presented below.

4.6.2 The Model

We first present a linear-integer programming model that simultaneously assigns land parcels to multiple uses. In this particular application we consider two uses only, namely conservation and military training. We then present alternative formulations, each incorporating a different spatial criterion to determine an optimal assignment of areas to conservation and military use given the spatial criterion. All the models that will be presented below have a common feature in that they employ a uniform grid partition of the area under consideration. Each grid square represents a land parcel, which will be referred to as 'site', which is assumed to be an independent decision unit. In all of the models selected areas are characterized by a central site and a set of sites clustered around that central site. Each such cluster is considered to be a reserve. The problem is then to determine the central site of each reserve (cluster) and assignment of individual sites to the center in an endogenous way while satisfying the conservation and military requirements. For each specification of the spatial criteria considered in site selection, we formulate a linear integer program involving binary variables each signifying whether the corresponding site is selected or not. The procedures and algebraic details of those models are described explicitly below.

We denote the set of all parcels in the area by L and denote individual parcels by l and k, where l identifies parcels chosen as centers of the reserves and k is used for all parcels. Parcel selection and assignment to a selected cluster is represented by a binary variable X_{lkt}, where X_{lkt} =1 if parcel k is selected and belongs to the cluster of type t centered at parcel l and X_{lkt} =0 otherwise. Note that, by construct, X_{llt} =1 for all cluster centers of type t, i.e. the central site of each cluster of type t belongs to that cluster. The symbol d_{lk} denotes the distance between parcel l and parcel k.

We first address the problem of constructing n_t compact clusters of type t, each covering a minimum area or sustainable population of θ_t or γ_t respectively and collectively covering a minimum area or population of Θ_t or Γ_t respectively. Here we define compactness of a reserve as the overall 'closeness' of all sites in it. There is no universally accepted measurement of compactness. We measure compactness by the sum of distances from all sites to the central site in each cluster, which must be minimized to the extent possible[67]. An algebraic model that serves this purpose, which will be referred to as the '*Base Model*' from here on, is given below.

[67] Compactness is not a well-defined concept. Note that the absolute value of the compactness measure defined here may not mean much just by itself, rather it has to be considered together with the size of the reserve (number of sites involved). This is because a reserve with only a few distant sites may have a smaller total distance value than a reserve with too many tightly packed sites, whereas in practice the latter should be considered more compact. Although not being fully satisfactory, this definition well serves the specific purposes of the present study. Minimizing the total distance typically results in a circular and connected reserve configuration.

$$
\begin{aligned}
&Min \sum_t \alpha_t \sum_l \sum_k X_{lkt} * d_{lk} \\
&s.t. \\
&i) \sum_l X_{llt} = \eta_t \quad \forall t \\
&ii) \sum_t \sum_l X_{lkt} \leq 1 \quad \forall k \\
&iiia) \sum_k X_{lkt} \geq X_{llt} * \gamma_t \quad \forall l, \forall t \\
&iiib) \sum_k X_{lkt} * e_{kt} \geq X_{llt} * \theta_t \quad \forall l, \forall t \\
&iva) \sum_l \sum_k X_{lkt} \geq \Gamma \quad \forall t \\
&ivb) \sum_l \sum_k X_{lkt} * e_{lt} \geq \Theta \quad \forall t \\
&v) X_{lkt} \leq X_{llt} \quad \forall l, \forall k, \forall t
\end{aligned}
$$

The objective function minimizes the sum of distances from all parcels in a cluster to the cluster's center, summed over all clusters of all types. The symbol α_t represents the priority (weight) given to the compactness of reserve type *t*. If compactness of certain types of reserves is preferred over others they are given a higher α value. The minimization of the sum of distances to central sites would lead to tightly packed clusters, thus compact reserves.

As mentioned above, a cluster is formed around site *l* if and only if X_{llt} =1. Therefore, constraint i) ensures that η_t clusters of type *t* have to be formed, where η_t is specified exogenously. Constraint ii) ensures that each parcel may belong to at most one center of any type. [68]

Constraint iii) ensures that each reserve area exceeds the minimum size. This constraint can be expressed in terms of a minimum number of parcels or land area (denoted by γ_t), as in

[68] Thus, the model does not allow overlapping of reserve areas of different types. If shared reserve areas are acceptable then this constraint should be eliminated.

constraint iiia), or in terms of a minimum population, as in constraint iiib), where θ_t and e_{kt} represent the minimum viable population level and the existing population of type *t* in parcel *k,* respectively.

Constraint iv) reflects similar requirements except that the restrictions are stated for the collection of all reserves instead of individual reserves. Γ_t is a parameter for the minimum desired reserve area in terms of land area for type t and Θ_t is a parameter for the minimum desired population of the total reserve of type t. Finally, constraint v) establishes the relationship between parcel assignment and center selection, namely parcel *k* can belong to a reserve centered at parcel *l*. for type t, i.e. $X_{lkt} = 1$, only if $X_{llt} = 1$. The model as specified will select clustered areas for multiple types of uses. No budget constraint is taken into account in this particular application. However, the model can be extended in a straightforward manner to include a budget constraint or by adding the cost of purchased or leased lands in the objective function after multiplying by a 'penalty' parameter signifying the importance of financial considerations[69].

Next we present the *meta-clustering model* which extends the base model to incorporate meta-clustering considerations. Such considerations may come in various forms.

[69] The budget constraint and the cost minimization component.

$$\boxed{\begin{array}{l} Min \sum_t \alpha_t \sum_l \sum_k X_{lkt} * d_{lk} + \beta \sum_k p_k * \sum_t \sum_l X_{lkt} \\ s.t. \quad vi) \sum_k p_k * \sum_t \sum_l X_{lkt} \le b \end{array}}$$

In the above extension β represents the weight given to the cost minimization component of the objective function, b represents the budget available and p_k is the cost of including parcel k in the selected cluster. If the costs per parcel changes by the type of use, then the cost component becomes $\sum_t p_{kt} \sum_l X_{lkt}$, where p_{kt} represents the cost of selecting parcel k for a cluster of type t.

For instance, one may want habitat clusters to be located close to or far from each other. Both approaches are meaningful since close clusters facilitate interaction between multiple populations in those areas while far apart clusters provide assurance against the spread of possible epidemics and therefore increases the likelihood of species survival. Each of these cases can be modeled conveniently. In this particular application having habitat clusters close to each other and military clusters close to each other is assumed to be a good thing. Also, moving the habitat clusters away from military clusters is also assumed to be desirable so as to minimize the adverse impacts of military training on habitat sites. We present a modification of the base model below that will place the habitat clusters away from military clusters[70].

$$Min \sum_{t} \alpha_t \sum_{l} \sum_{k} X_{lkt} * d_{lk}$$

$s.t.$ Constraints i through v same as specified in the Base Model

$$via) d_{lk} \geq (X_{llt1} + X_{kkt2} - 1) * \bar{d} \quad \forall l, \forall k$$

The objective function and the individual constraints i – v are identical to those of the base model. Constraint *via)* is restrictive only when $X_{llt} = X_{kkt} = 1$, namely parcels *l* and *k* are cluster centers of type t1 (habitat) and type t2 (military), in which case the two cluster centers cannot be close to each other by less than $\bar{d}$.

Finally, we present the *proximity-to-roads* model a modification to the base model that incorporates the distance between cluster centers and the roads network. This modification

[70] One may also want to restrict the relative locations of clusters of the same type. For instance, any two clusters may be desired to be away from each other by at least a given distance $\bar{d}$. Alternatively, one may want any pair of clusters to be close to each by less than a certain distance $\bar{d}$ (this is an important consideration in conservation reserve design as it reduces habitat fragmentation). These considerations can be incorporated by augmenting the following equations, respectively, to the above model:

$$vib) d_{lk} \geq (X_{llt} + X_{kkt} - 1) * \bar{d} \quad \forall l, \forall k, \forall t$$

$$vic) d_{lk} * (X_{llt} + X_{kkt} - 1) \leq \bar{d} \quad \forall l, \forall k, \forall t$$

aims to place military clusters close to the roads and habitat clusters away from the roads. The purpose here is to maximize accessibility to the military training areas by roads, while minimizing the disturbance caused by military traffic on habitat areas. This can be done by using a simple constraint similar to vi) above. Alternatively, the distances from each cluster to the nearest road can be incorporated in the objective function to reward or penalize proximity. Here we chose the second alternative. The modified objective function is given below:

$$\boxed{\begin{array}{l} Min \sum_{t} \alpha_t \sum_{l} \sum_{k} X_{lkt} * d_{lk} + \sum_{t} \beta_t \sum_{l} X_{llt} * r_l \\ s.t. \\ \text{Same constraints as Base Model} \end{array}}$$

The objective function has two additional terms that incorporate the distance to roads. The term $\sum_{l} X_{llt_{military}} * r_l$ is the sum of distances from military cluster centers to the closest roads, where r_l is the distance from parcel *l* to the nearest road, and $\sum_{l} X_{llt_{habitat}} * r_l$ gives the sum of the distances from habitat cluster centers to the closest roads. The parameters α_t, and β_t reflect the relative weights assigned to compactness and proximity to the roads. Using a positive value for β would select military areas that are closer to roads while using a negative value for habitat areas would do the opposite. Since military clusters are aimed to be located close to roads and habitat clusters should be located away from roads, in this application we choose $\beta_{military} > 0$ and $\beta_{habitat} < 0$. The results for the above models are presented and discussed in the result section below.

4.6.3 Data

Suitability maps for military armor training areas and GT habitat training were generated using the GRASS raster GIS processing software. The habitat map was based on the Red-Cockaded Woodpecker and Gopher Tortoise habitat maps developed by the Georgia Gap Analysis Program (Elliot et al. 2003). At a 30-meter resolution, areas suitable for both were given a value of 2, for either a value of 1, and for neither a value of 0.[71][72] The armor training suitability map was based on the Georgia GAP analysis' National Land Cover Data (NLCD) map, a soils map, a digital elevation model (DEM), and a current military landuse map. Each NLCD category was associated with a suitability to directly support training and with a maximum traversal speed. The speed map was then analyzed with the GRASS r.cost program to identify the minimum travel time from a proposed armor parking area to every location across the installation. A soil K-factor was extracted from the soils map, slope from the DEM, and military use index from the military land use map. The armor suitability was then calculated for each location with this equation:

$$\boxed{armor\ suitability_i = travel\_time_i^2 \times military\_use_i \times land\_use\_index_i \times k\_factor_i^2 \times slope\_index_i}$$

All analysis to this point was accomplished at a 30x30m resolution. The above raster files were converted to ESRI shape files using ARC GIS 9.2. A 30x30 grid file, where each grid was approximately 1200m by 1200m[73] was created using Geoda and the grid shape file was spatially joined with the above shape files using the spatial join tool in ARC GIS. The spatial join gives the grid file the attributes of the shape file. To ensure that each grid cell represents a density of the

[71] The ecological suitability parameter is assumed to be independent across sites, a standard assumption in the reserve site selection literature.
[72] In a single species analysis the simplest measure of habitat suitability can be the carrying capacity, namely the maximum number of individuals that can be supported by each site, depending on the soil types, vegetation, access to water sources, slopes and various other physical and ecological considerations. When multiple species are involved a different suitability index needs to be defined for each site and each species (for an example see Cowling et al. 2003). In this case, the second summation in the objective function (total suitability) needs to be modified where suitability is summed across the species as well (using possibly differential weights).
[73] The area under consideration is 35,658 meters (22 miles) across and each parcel is 1188 meters (3/4 of a mile) across.

original data, the “sum” option was used when joining the suitability data. The suitability grid files and the values are shown in Figure 4.16 (c) and Figure 4.16(d). The current Ft. Benning base area is given in Figure (a). The current analysis considers suitability areas both inside and outside -but near the boundary- the base area[74]. An ESRI Shape file of roads for the area under consideration was used to obtain information about the roads in Ft. Benning for the proximity-to-roads model. Only interstate highways, four-lane highways and two-lane highways were considered in the analysis[75]. The road information is shown in Figure 4.16 (b). The Euclidean distances between the centroid of each cell and the centroid of the cell containing the closest road segment was used as the minimum distance from that cell to the road network.

The grid cell values for habitat suitability, Figure 4.16 (c), are specified using a suitability index with values ranging from 1 to 6. The values were aggregated from the 30 meter

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[74] If necessary, it is possible to either give higher preference to suitability areas within the base area or to not consider the areas outside the base area.

[75] Given the current working resolution of 1200m x 1200m grid cells, including smaller roads leads to too many roads being present in most cells which implies that it is not possible to find areas that are sufficiently away from the roads.

resolution maps. The original values were based on soil type, land cover, and suitability for gopher tortoise. The grid cell values for military suitability, Figure 4.16 (d), are specified using a suitability index with values ranging over 1-12. These values were obtained by aggregating the original data provided by Ft. Benning and the original values were based on slope, vegetation, soils type. The results for the models described above are presented below.

4.6.4 Results and Discussion

We solved the base model and its extensions for different specifications of the number of clusters of each type. The results for the base model for one cluster, two clusters and four clusters are displayed in Figure 4.17. For the remainder of the analysis we present the results only for two clusters of each type (scenario-1) and four clusters of each type (scenario-2). For scenario-1, we imposed a minimum suitability index of 50 for each cluster and a total suitability of 150; for scenario-2, we imposed a minimum suitability index of 50 for each cluster and a total suitability of 250. These suitability indexes are specified arbitrarily, rather than being actual specifications to be implemented, to demonstrate how the model responds to such variations in policy (model) parameters.

The results of the base model for two and four clusters are displayed in Figure 4.18a) and 3d). In both cases the model chooses fairly compact clusters for each type. In Figure 4.18a) the model selects two habitat clusters with 9 and 6 parcels and two military clusters with 17 and 16 parcels. Figure 4.18(d) shows the results for four habitat clusters and four military clusters. The military clusters are located close to each other in the central part of the area under consideration while the habitat clusters are located both away from the military clusters and away from each other. The only exception is habitat cluster 3 which is located in the middle of the selected military areas. As mentioned earlier placement of the habitat areas away from the military training areas is considered as a desirable property since this would minimize the adverse impact of military training on habitat clusters. The outcome we observe here is a result of the particular data set used rather than a model driven configuration. For other data sets it is possible that habitat clusters can be adjacent to military clusters or can be close together, which may not be desirable. In such cases the model can be modified accordingly to incorporate such proximity considerations and promote desirable cluster configurations.

Figure 4.18 b-c) and Figure 4.18 e-f) display the results under minimum inter-cluster distance criteria as imposed by constraint *via)*. (i.e. clusters of a different types must be located away from each other). The results clearly highlight the functioning of the constraint. Note that, when the additional criterion is imposed or the distance limitation is made more stringent (i.e. a higher $\bar{d}$ value), the number of selected parcels increases and the resulting clusters are not as compact. In the base case (Figure 4.17a), all clusters are contiguous and a total of 29 habitat parcels and 60 military parcels are selected while in Figure 4.18.f), where the largest inter-cluster distance is imposed, there are non-contiguous clusters and 30 habitat parcels and 66 military parcels are selected.

Figure 4.19 displays the results of the proximity–to-roads model. Ideally military clusters should be located close to roads and habitat clusters should be located away from roads. As can be seen in the base run solution (Figure 4.18a) the military areas are placed close to the roads but the habitat areas also are placed adjacent to the roads. In particular habitat cluster 2 is intersected by a road segment. As mentioned in the model a negative weight on the proximity to weight component of the objective function will move the clusters away from the roads and a positive weight will move the clusters towards the roads. For all the proximity-to-roads runs the weights on the clustering component of the objective function were fixed at 0.5 for both habitat and military clusters. In panel (b) the proximity-to-roads component for the habitat clusters had a weight of -1 and the corresponding weight for the military clusters was 1. These weights were increased to -10 and 10 in panel (c) and -20 and 20 in panel (d). The location of the military clusters does not change significantly since they were initially located adjacent to the roads. As the panels (a) through (d) indicate a higher weight on the total distance for habitat clusters from roads moves those clusters away from the roads. At the same time since a larger weight is being placed on the proximity-to-roads component of the objective function the relative weight on clustering decreases and these causes the larger and non- contiguous habitat clusters shown in the figure.

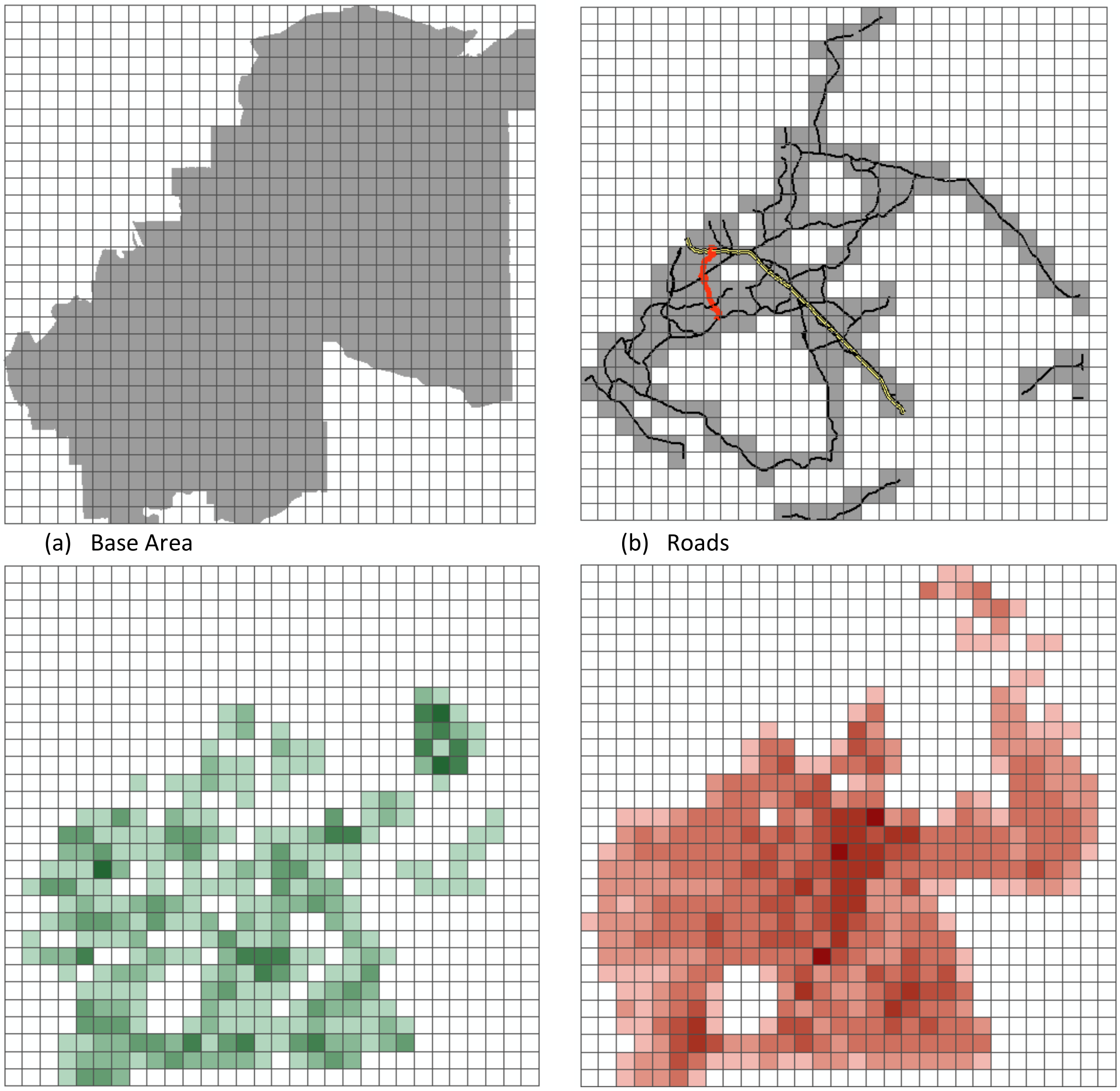
4.6.5 Conclusion

The methods presented in this paper extend the reserve design literature by presenting a model that can consider multiple land uses simultaneously where selected parcels are desired to form clusters, each serving a particular purpose (such as conservation and military areas or open space and urban development). We then provide extensions to the model to incorporate meta-clustering considerations such as distance between selected clusters and proximity of clusters to specified features (such as roads or water bodies). As the results indicate the extensions are able to generate solutions that contain the desired spatial configurations. It should be noted that adding the spatial requirements may force the model to select from among less suitable parcels when the best parcels do not meet the specified spatial criteria. This, in general, leads to the selection of a larger number of parcels for each cluster and may also reduce the compactness of individual clusters. This is most evident in the proximity-to-roads model results, where, as shown in Figure 4.19 (panels c and d), non-compact sites were selected for one cluster. This is to be expected since the additional constraints reduce the decision space (set of feasible parcels), which in turn leads to a less compact optimal configuration. For scenarios that require higher resolution results, it is possible to conduct a nested analysis, where low resolution data is used to locate the general area and higher resolution data for the surrounding area is used to identify the specific areas.

Finally, it should be mentioned that this paper is more than an empirical analysis of GT conservation in a military area. By successfully incorporating ecological and spatial consideration into linear site selection models, we illustrate that it is possible to obtain robust conservations reserves using integer programming. The methods introduced are applicable to many other endangered and at risk species and can be extended to include multiple species and multiple land uses. We are currently working on an extension that incorporates the symbiotic relationships between species where we identify the suitable conservation areas for both Gopher Frog and Gopher Tortoise. In addition, we hope the results illustrate that other forms of spatial and ecological constraints can be successfully incorporated into linear site selection models. Further, with appropriate modifications the methods introduced in this paper can be applicable to many other problems of land use/allocation, such as optimal selection of nature reserves, districting problems (political districting, school districting, business districting), or optimal urban expansion.

4.6.6 Figures

Figure 4.16- The study area, road network, and habitat suitability index and military suitability index indicators*



(a) Base Area

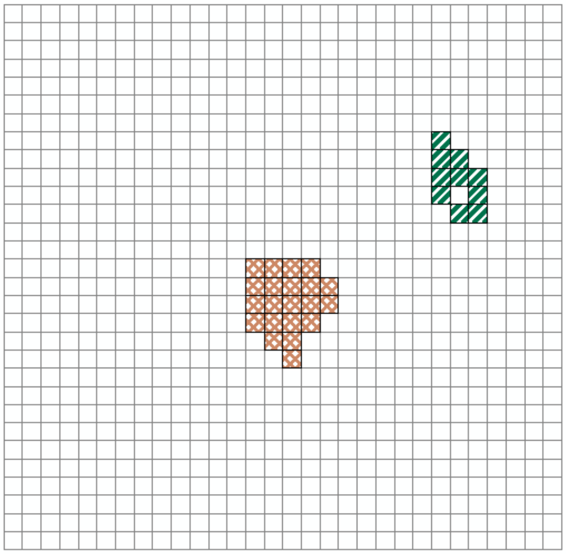
(b) Roads

(c) Habitat Suitability Index

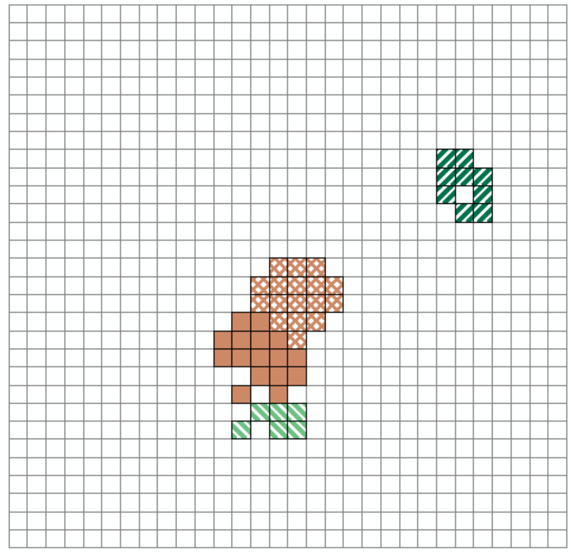
(d) Military Suitability Index

*darker shades indicate higher suitability

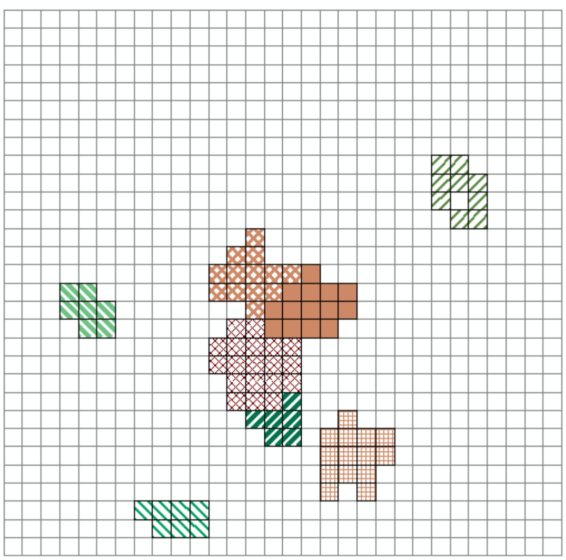
Figure 4.17 – Base model results



(a) 1 habitat cluster and 1 military cluster



(b) 2 habitat clusters and 2 military clusters



(c) 3 habitat clusters and 3 military clusters

Figure 4.18 – Results of the base model with two and four cluster selections and separation of military and habitat clusters

(a) Base model results

(b) Minimum distance between clusters = 10

(c) Minimum distance between clusters = 20

(d) Base model results

(e) Minimum distance between clusters = 10

(f) Minimum distance between clusters = 15

Figure 4.19- Results of the proximity-to-roads model

(a) Habitat weight = 0, military weight = 0

(b) Habitat weight = -1, military weight = 1

(c) Habitat weight = -10, military weight = 10

(d) Habitat weight = -20, military weight = 20

*A negative weight moves clusters away from roads, a positive weight moves clusters towards roads.

4.7. References

Ando, A., Camm, J., Polasky, S. and Solow, A. 1998. Species distributions, land values, and efficient conservation. Science. 279, 2126.

Araújo, M.B., Cabeza, M., Thuiller, W., Hannah, L. and Williams, P.H. 2004. Would climate change drive species out of reserves? An assessment of existing reserve-selection methods. Global Change Biol. 10, 1618-1626.

Ashton, P.S. and Ashton, R.E. 2004. The gopher tortoise: a life history. Pineapple Press Inc, .

Assessment, M.E. 2005. Millennium ecosystem assessment. Ecosystems and Human Well-Being: Synthesis.

BenDor, T., Westervelt, J., Aurambout, J.P. and Meyer, W. 2009. Simulating population variation and movement within fragmented landscapes: An application to the gopher tortoise (Gopherus polyphemus). Ecol.Model. 220, 867-878.

Benton, N., Ripley, J.D. and Powledge, F.(eds.). 2008. Conserving Biodiversity on Military Lands: A Guide for Natural Resources Managers. NatureServe, Arlington, Virginia, .

Bevers, M., Hof, J., Uresk, D.W. and Schenbeck, G.L. 1997. Spatial optimization of prairie dog colonies for black-footed ferret recovery. Oper.Res. 45, 495-507.

Burns, C.E., Johnston, K.M. and Schmitz, O.J. 2003. Global climate change and mammalian species diversity in US national parks. Proc.Natl.Acad.Sci.U.S.A. 100, 11474.

Cabeza, M. 2003. Habitat loss and connectivity of reserve networks in probability approaches to reserve design. Ecol.Lett. 6, 665-672.

Camm, J.D. 1996. A note on optimal algorithms for reserve site selection. Biol.Conserv. 78, 353-355.

Cerdeira, J.O., Gaston, K.J. and Pinto, L.S. 2005. Connectivity in priority area selection for conservation. Environmental Modeling and Assessment. 10, 183-192.

Cerdeira, J.O. and Pinto, L.S. 2005. Requiring connectivity in the set covering problem. Journal of combinatorial optimization. 9, 35-47.

Church, R.L., Stoms, D.M. and Davis, F.W. 1996. Reserve selection as a maximal covering location problem. Biol.Conserv. 76, 105-112.

Cova, T.J. and Church, R.L. 2000. Contiguity Constraints for Single-Region Site Search Problems. Geogr.Anal. 32, 306-329.

Dissanayake, S.T.M., Onal, H. and Westervelt, J.D. 2011. Optimum Selection of Conservation Reserves: Extensions to Multiple Land Use. Mil.Oper.Res. 16, 65-76.

Elliott, M., Anderson, L., Bumback, B., Schmidt, J.P. and Kramer, L. 2003. Gap Analysis Project: Georgia GAP reptile models. 2008, . http://gapanalysis.nbii.gov/. Last accessed on 06-25-2008.

Flather, C.H., Joyce, L.A. and Bloomgarden, C.A. 1994. Species endangerment patterns in the United States. General technical report RM (USA).

Flather, C.H., Knowles, M.S. and Kendall, I.A. 1998. Threatened and endangered species geography. Bioscience. 48, 365-376.

Garfinkel, R.S., Neebe, W., Rao, M.R. 1974. An algorithm for the m-median plant location problem. Transportation Science 8, 217–236.

Haight, R.G., Snyder, S.A. and Revelle, C.S. 2005. Metropolitan open-space protection with uncertain site availability. Conserv.Biol. 19, 327-337.

Halpin, P.N. 1997. Global climate change and natural-area protection: management responses and research directions. Ecol.Appl. 7, 828-843.

Hughes, L. 2000. Biological consequences of global warming: is the signal already apparent? Trends in Ecology & Evolution. 15, 56-61.

Kirkpatrick, J. 1983. An iterative method for establishing priorities for the selection of nature reserves: an example from Tasmania. Biol.Conserv. 25, 127-134.

Kostreva, W. 1999. Relocation problems arising in conservation biology. Comput.Math.Appl. 37, 135-150.

Lawler, J.J. 2009. Climate change adaptation strategies for resource management and conservation planning. Ann.N.Y.Acad.Sci. 1162, 79-98.

Lichtenstein, M.E., Montgomery, C.A. 2003. Biodiversity and timber in the Coast Range of Oregon: inside the production possibility frontier. Land Economics 79, 56–73.

Lubow, B.C. 1996. Optimal translocation strategies for enhancing stochastic metapopulation viability. Ecol. Appl. 6, 1268-1280.

Margules, C.R. and Pressey, R.L. 2000. Systematic conservation planning. Nature. 405, 243-253.

Margules, C., Nicholls, A. and Pressey, R. 1988. Selecting networks of reserves to maximise biological diversity. Biol.Conserv. 43, 63-76.

Martinez-Meyer, E. 2005. Climate change and biodiversity: some considerations in forecasting shifts in species' potential distributions. Biodiversity Informatics. 2, 42-55.

McCarty, J.P. 2001. Ecological consequences of recent climate change. Conserv.Biol. 15, 320-331.

Moilanen, A., Franco, A., Early, R.I., Fox, R., Wintle, B. and Thomas, C.D. 2005. Prioritizing multiple-use landscapes for conservation: methods for large multi-species planning problems. Proceedings of the Royal Society B: Biological Sciences. 272, 1885.

Nalle, D.J., Arthur, J.L., Montgomery, C.A. and Sessions, J. 2002. Economic and spatial impacts of an existing reserve network on future augmentation. Environmental Modeling and Assessment. 7, 99-105.

Nicholls, A. and Margules, C. 1993. An upgraded reserve selection algorithm. Biol.Conserv. 64, 165-169.

Önal, H., and Briers, R.A. 2002. Incorporating spatial criteria in optimum reserve selection. Proceedings of the Royal Society of London B, 269 2437-2441.

Önal, H., and Briers, R.A. 2003. Selection of a minimum boundary reserve network using integer programming. Proceedings of the Royal Society of London B 270 1487-1491.

Önal, H., and Briers, R.A. 2005. Designing a conservation reserve network with minimal fragmentation: a linear integer programming approach. Environmental Modeling and Assessment 10, 193–202.

Önal, H. and Wang, Y. 2008. A Graph theory approach for designing conservation reserve networks with minimal fragmentation. Networks 52 142-152.

Orth PB, Warren S.D. 2006. Disturbance-dependency of threatened and endangered species found on US Army lands. CEMML TPS 06-17. Colorado State University Environmental Management of Military Lands. Fort Collins, CO. Parmesan, C. and Yohe, G., 2003. A globally coherent fingerprint of climate change impacts across natural systems. Nature. 421, 37-42.

Polasky, S., E. Nelson, E. Lonsdorf, E., Fackler, P. and Starfield, A. 2005. ―Conserving Species in a Working Landscape: Land Use with Biological and Economic Objectives. Ecological Applications 15: 1387-1401.

Polasky, S., Nelson, E. Camm, J., Csuti, B., Fackler, P., Lonsdorf, E., White, D., Arthur, J., Garber-Yonts, B., Haight, R., Kagan, J., Montgomery, C., Starfield, A., and Tobalske, C. 2008. ―Where to Put Things? Spatial Land Management to Sustain Biodiversity and Economic

Production. Biological Conservation 141(6): 1505-1524.

Possingham, H., Ball, I. and Andelman, S. 2000. Mathematical methods for identifying representative reserve networks. Quantitative methods for conservation biology. 291-306.

Pressey, R., Humphries, C., Margules, C., Vane-Wright, R. and Williams, P. 1993. Beyond opportunism: key principles for systematic reserve selection. Trends in ecology & evolution. 8, 124-128.

Pressey, R., Possingham, H. and Day, J. 1997. Effectiveness of alternative heuristic algorithms for identifying indicative minimum requirements for conservation reserves. Biol. Conserv. 80, 207-219.

Rodrigues, A.S.L. and Gaston, K.J. 2002. Optimisation in reserve selection procedures--why not? Biol.Conserv. 107, 123-129.

Root, T.L., Price, J.T., Hall, K.R., Schneider, S.H., Rosenzweig, C. and Pounds, J.A. 2003. Fingerprints of global warming on wild animals and plants. Nature. 421, 57-60.

Saunders, S., Easley, T., Logan, J.A. and Spencer, T. 2007. Losing ground: Western national parks endangered by climate disruption. The challenges of climate change. 24, 1-41.

Stein, B.A., Scott, C. and Benton, N. 2008. Federal lands and endangered species: the role of military and other federal lands in sustaining biodiversity. BioScience 58:339–347.

Tenhumberg, B., Tyre, A.J., Shea, K. and Possingham, H.P. 2004. Linking wild and captive populations to maximize species persistence: optimal translocation strategies. Conserv.Biol. 18, 1304-1314.

Tóth, S.F., Haight, R.G., Snyder, S.A., George, S., Miller, J.R., Gregory, M.S. and Skibbe, A.M. 2009. Reserve selection with minimum contiguous area restrictions: An application to open space protection planning in suburban Chicago. .

Underhill, L. 1994. Optimal and suboptimal reserve selection algorithms. Biol.Conserv. 70, 85-87.

Vane-Wright, R.I., Humphries, C. and Williams, P. 1991. What to protect? Systematics and the agony of choice. Biol.Conserv. 55, 235-254.

Walther, G.R., Post, E., Convey, P., Menzel, A., Parmesan, C., Beebee, T.J.C., Fromentin, J.M., Hoegh-Guldberg, O. and Bairlein, F. 2002. Ecological responses to recent climate change. Nature. 416, 389-395.

Williams, J. C. and ReVelle C.S. 1998. Reserve assemblage of critical areas: A zero-one programming approach. European Journal of Operational Research 104 497-509.

Williams, J. C., ReVelle, C. S. and Levin, S. A. 2005. Spatial attributes and reserve design models: a review. Environmental Modeling and Assessment 10:163–181.

Young, H. P. 1988. Measuring the compactness of legislative districts. Legislative Studies Quarterly, 13, 105-115.

Zhou, S.R. and Wang, G. 2006. One large, several medium, or many small? Ecol. Model. 191, 513-520.

5. Appendix

5.1. Appendix A

The notation used in the algebraic model is as follows: S_{tk} denotes whether site *k* is selected in period *t*, specifically S_{tk}=1 if site *k* is selected in period *t* and S_{tk}=0 otherwise; Y_k identifies whether a site adjacent to site *k* is selected in period 1, in which case Y_k =1, and Y_k=0 otherwise; A_k identifies whether site *k* selected in the second time period is subject to a higher purchase price, specifically A_k =1 if site *k* is purchased in period 2 and an adjacent site to it is selected in period 1, A_k =0 otherwise; X_{ik1}, X_{ik2} identify the reserve assignments of selected sites, specifically X_{ikt}=1 if site *k* is assigned to a reserve centered at site *i* in period *t* and X_{ikt}=0 otherwise. Note that if site i is a center of a cluster formed in period t, then X_{iit}=1, meaning that each cluster center is part of the cluster. The rest of the symbols denote constant parameters: p_{tk} , p_{ak} , b_t , and e_k represent the price of parcel *k* in period *t,* the price premium (that may vary across sites), the budget available in period *t* and the ecological suitability of parcel k, respectively. As discussed previously ecological suitability is a measure of the suitability of each land parcel for the conservation purpose under consideration and *n* represents the number of reserves (clusters) to be selected. For convenience and readability, the notation for some other scalars and parameters is introduced whenever they are referenced.

The full algebraic model is presented below.

Minimize $\alpha_1 \sum_i \sum_k X_{ik2} * d_{ik}$ $-\alpha_2 \sum_k (S_{1k} + S_{2k}) e_k$

Objective function: The first summation measures the compactness of reserves configured at the end of period-two; the second summation represents the total habitat suitability of sites selected in both periods.

s.t.

1) $\sum_i X_{ii2} = n$

1): imposes the number of required clusters.

2) $\sum_i X_{ikt} \leq 1 \quad \forall k, t$

2): each site is assigned to at most one cluster.

3) $X_{ikt} \leq X_{iit} \quad \forall i, k, t$

3): technical constraint for clustering

4) $X_{ik2} \geq X_{ik1} \quad \forall i, k$

4): maintains cluster assignments from period one to period two.

5) $\sum_k S_{1k} * p_{1k} \leq b_1$

5): budget constraint for period one.

6) $\sum_k S_{2k} * p_{2k} + \sum_k A_k * p_{ak} \leq b_2$

6): budget constraint for period two.

7) $S_{1k} = \sum_i X_{ik1} \quad \forall k$

7): If a site is assigned to any reserve in period one then it must be selected in period one, namely $S_{1k} = 1$.

8) $S_{2k} = \sum_i \left(X_{ik2} \text{-} X_{ik1} \right) \quad \forall k$

8): Same as 7), but stated for period two.

9) $\mathrm{m}Y_k \geq \sum_{j \in N(k)} S_{1j} \quad \forall k$

9): Determines whether a neighbor of site k selected in period two was selected in period one, namely $Y_k = 1$.

10) $A_k \geq S_{2k} + Y_k - 1 \ \forall k$

10): Determines whether parcel k selected in period two is subject to a higher second period price, namely $A_k = 1$ if site k is adjacent to some site selected in period one.

$X_{ikt}, Y_k = 0,1 \quad \forall i, k, t$

$S_{tk}, A_k \geq 0 \quad \forall k, t$

The objective function, $\alpha_1 \sum_i \sum_k X_{ik2} * d_{ik} - \alpha_2 \sum_k (S_{1k} + S_{2k}) e_k$, consists of two components. The first summation represents the total distance between the center of each reserve and the sites assigned to that reserve, summed over all reserves. The second summation term is the amount of ecological suitability of the selected sites in the first and second period[76]. To unify these two non-compatible objectives in a conventional optimization framework a weighted average of the two objectives is considered where the symbols α_1 and α_2 denote the weights assigned to the two objectives.

Constraint (1) imposes the condition that at the end of period 2 exactly *n* clusters must be formed, where *n* is specified exogenously by the conservation agency. Constraint (2) implies that each site can belong to at most one cluster.

Constraints (3) and (4) govern the cluster formation (i.e. assignment of each selected site to a cluster formed by the selected sites). Specifically, constraint (3) implies that if site *k* is selected and assigned to site *i* in period *t*, then a cluster centered at site *i* must be formed in that period. We assume that the first period selections and reserve configurations are maintained in the second period; that is if a site is selected and assigned to a given reserve in period one, then it is assumed to be selected and assigned to the same reserve in period two also.[77] This is governed by constraint (4) which implies that if a site is assigned to a cluster in period 1, the same assignment is maintained in period 2.

Constraints (5) and (6) represent the budget restrictions for period one and two, respectively. Currently we assume that budget carry over is not possible, but the model can be

[76] As formulated the model does not include any minimum viable population requirement, but such constraints can be incorporated easily for individual reserves as well as the entire reserve system as follows:

11) $\sum_k X_{ik2} * e_k \geq vp \quad \forall i$ 12) $\sum_i \sum_k X_{ik2} * e_k \geq tp \quad \forall i$

where *vp* is the minimum sustainable population for one reserve and *tp* is the minimum total population to be protected in the entire reserve network.

[77] It is possible to allow for sites selected in the first period to be sold in the second period, but we choose to not allow for this since in practice conservation agencies make long term purchases.

modified in a straight forward way to incorporate carry over possibility[78] . Constraints (7) and (8) ensure that a site is selected if and only if it is assigned to a reserve.[79]

Constraints (9) and (10) are of central importance in the model. Together these constraints endogenously identify the second period sites that are adjacent to first period selections. Constraint (9) identifies if any site adjacent to site *k* is selected in the first period. The set N(k) denotes the neighbors of site k and m is an arbitrarily selected large number[80]. If any site adjacent to site k is selected in the first period, then the summation $\sum_{n \in N(k)} S_{1n}$ will be positive and Y_k is forced to be greater than zero, but since Y_k is defined as a binary variable Y_k =1. Constraint (10) identifies the second period selections that are subject to a higher price, namely if they are adjacent to some sites selected in the first period.

It should be noted that we define S_{tk} and A_k as non-negative variables, instead of binary variables, but because of the model structure these variables can assume only binary values.[81]

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[78] Budget carry-over possibility can be modeled by modifying constraint (6) as follows

$$\sum_l S_{2l} * p_{2k} + \sum_l SA_l * p_{pk} \le b_2 + (b_1 - \sum_l S_{1l} * p_{1k})$$

To consider discounting, the second term on the right hand side needs to be multiplied by one plus the interest rate.

[79] Constraints (7) and (8) imply that if site *k* is assigned to reserve *i* in any period then it must be selected in that period, i.e., if X_{ik1} = 1 for some *i* (from (2) there can be at most one such *i*) then S_{1k} = 1 and if X_{ik2} = 1 then S_{2k} = 1

[80] The scalar m is an arbitrary large number which signifies an overestimate of the number of sites that can be included in a cluster.

[81] The reasons are as follows. Constraint (7) and (8) imply that S_{tk} is either 0 or 1 depending on the value of the summation on the right hand side, which can be either 0 or 1 because of (2). Likewise the value of A_k has to be binary under all combinations of S_{2k} and Y_k because of (10) and (6). The model chooses the least possible value A_k since this variable uses a positive amount of budget without having any contribution to the objective function. Therefore, if S_{2k} = Y_k =1, then A_k =1, otherwise A_k=0. Defining S_{tk} and A_k as non-negative variables is crucial for the model's computational efficiency since when solving linear integer programming problems with more binary variables typically increase the computational complexity.

5.2. Appendix B – Discussion of uncertainty

As discussed in Section 2, development uncertainty has been incorporated into reserve design models using Stochastic Dynamic Programming and two-period integer programming, therefore the model presented here did not incorporate development uncertainty. Snyder et al. model the uncertainty in development with a set of probabilistic scenarios where each site has a 50% possibility of being developed in period two. In this section we simulate uncertainty of site availability to study the value of incorporating amenity price effects in the presence of uncertainty.[82] The method used for the Monte-Carlo simulation allows us to simulate probabilistic development scenarios. First we assume a homogeneous development probability *p* drawn from a uniform distribution.[83] This implies that when the first period decisions are being the expected probability of a site being available in the second period is (*1-p*). Therefore the expected ecological benefit of a second period site is $(1-p)e_k$. We conduct the Monte-Carlo simulation as before with the following additions.

1. In the first period assume the second period ecological benefit is $(1-p)e_k$
2. At the start of the second period, randomly choose *p*S* sites that are unavailable
3. Solve the second period, the available sites *(S* (1-p) sites))* have ecological benefit e_k

By simulating the development uncertainty in this manner we are able to analyze the robustness of the above results to various levels of uncertainty. The results for a 10% development probability and 50% development probability for 500 runs is presented in Table 2.4. The results indicate that at low levels of uncertainty accounting for location based price

[82] The uncertainty we represent is the uncertainty that land will not have an ecological value in the next time period. This could either be due to development or to species becoming extinct. We do not differentiate between these types of uncertainty.

[83] This uncertainty can also be interpreted as probability of species extinction.

premiums provides superior results; the two-period model continues to perform better than the iterated one-period model. As the level of uncertainty increases, the advantage in accounting for price effects decreases. This is an expected result since the increasing uncertainty levels decrease the advantage that the forward looking model has over the myopic model. Therefore we conclude that accounting for location based price premiums will only give superior results at low levels of development uncertainty.

5.3. Appendix C: Survey Design for 7 attributes

Set	x1	x2	x3	x4	x5	x6	x7	Set	x1	x2	x3	x4	x5	x6	x7	Set	x1	x2	x3	x4	x5	x6	x7
1	2	1	2	3	1	2	6	19	1	1	2	1	3	3	1	37	3	3	1	2	2	2	5
	1	2	1	2	3	1	4		2	3	1	3	1	1	4		2	1	2	1	1	3	4
2	3	1	2	2	3	1	5	20	2	2	3	1	3	2	4	38	1	2	3	3	2	1	1
	2	2	1	1	2	3	2		1	1	1	3	1	1	2		2	3	2	2	3	2	2
3	2	3	2	1	2	3	5	21	3	3	3	1	3	1	6	39	3	3	2	3	3	3	3
	1	2	1	2	3	1	4		2	2	1	3	1	2	5		2	1	3	1	2	1	5
4	3	3	1	2	1	3	2	22	1	2	1	2	3	1	4	40	1	3	1	3	3	2	1
	2	2	3	1	3	2	4		2	3	3	3	2	2	3		2	2	3	2	1	3	6
5	1	3	1	1	2	3	3	23	2	1	1	2	3	2	1	41	1	1	1	3	1	1	2
	3	2	2	2	1	2	6		1	3	3	1	1	1	5		2	2	3	1	3	2	4
6	1	1	3	3	3	3	6	24	1	1	2	2	2	1	3	42	2	1	1	2	2	3	3
	3	3	1	2	2	2	5		3	2	3	3	3	3	5		1	2	2	1	1	2	2
7	2	2	2	3	2	1	1	25	2	3	2	1	2	3	5	43	3	2	2	2	1	2	6
	1	3	3	2	3	3	2		3	1	3	2	1	2	1		2	1	3	1	2	1	5
8	3	2	1	3	1	1	1	26	2	1	3	3	3	1	2	44	2	1	1	2	3	2	1
	1	1	3	2	2	2	4		1	2	1	2	2	3	6		3	2	2	1	2	3	4
9	3	3	2	1	1	1	1	27	1	3	1	3	3	2	1	45	2	1	2	3	1	2	6
	1	1	3	3	3	3	6		3	2	3	2	2	1	2		3	2	3	2	2	1	2
10	3	1	2	2	3	1	5	28	3	2	2	1	2	3	4	46	1	2	3	1	1	2	3
	2	2	1	1	2	3	2		2	1	3	3	3	1	2		3	1	1	3	3	3	4
11	3	1	2	3	2	2	2	29	2	2	2	2	3	1	3	47	3	3	3	3	2	2	4
	2	3	1	1	3	1	6		3	3	3	3	2	2	4		2	2	2	2	3	1	3
12	1	3	2	3	2	2	6	30	3	1	2	3	2	2	2	48	2	2	2	3	2	1	1
	3	1	3	1	1	3	3		2	3	3	2	1	3	1		3	1	3	1	1	3	3
13	3	2	3	3	3	3	5	31	1	2	3	1	1	2	3	49	1	2	2	3	3	3	5
	1	3	2	2	1	1	4		3	1	1	3	3	3	4		3	1	3	2	1	2	1
14	1	1	2	1	3	3	1	32	2	2	1	3	1	2	5	50	3	1	3	1	1	3	3
	2	3	3	3	2	2	3		1	1	2	2	2	1	3		2	3	2	2	3	2	2
15	2	1	1	2	2	3	3	33	3	3	2	1	1	1	1	51	1	2	3	3	2	1	1
	3	3	3	1	3	1	6		1	2	1	2	2	3	6		2	1	2	1	1	3	4
16	3	2	1	1	3	2	3	34	1	2	2	3	3	3	5	52	2	3	3	2	1	3	1
	2	3	3	2	1	3	1		3	1	1	1	2	1	6		3	2	1	1	3	2	3
17	3	3	2	3	3	3	3	35	1	1	3	2	2	2	4	53	1	3	3	2	3	3	2
	1	1	1	1	1	2	5		2	3	1	1	3	1	6		3	1	1	1	2	1	6
18	2	3	1	3	1	1	4	36	2	2	1	1	2	3	2	54	2	2	2	3	2	1	1
	1	1	2	1	3	3	1		1	3	2	2	1	1	4		1	1	1	1	1	2	5

5.4. Appendix D: The survey

Choice Question 1

Suppose Option A and Option B were the **only** grassland projects you could choose. Which **one** would you choose? Please read **all** the features of **each** option and then **check the box that represents your choice**. If you do not like either option A or option B, then please choose the box marked “No grassland project” which is Option C.

Attribute	**Number of Bird Species**	**Density of Birds**	**Number of endangered species**	**Amount of wildflowers.**	**Use of prescribed fire.**	**Distance to restored area**	**Annual cost to your household**	**I would Choose**
Option A	20 different species	5 individuals per acre	3 endangered or threatened species	60% covered in wildflowers	No prescribed burning	50 miles	$100	❒ A
Option B	10 different species	10 individuals per acre	0 endangered or threatened species	40% covered in wildflowers	Prescribed burning once every year	10 miles	$70	❒ B
Option C	No Restoration Project						No cost	❒ C